Data Analytics in Financial Due Diligence – A Mixed Methods Approach to Use and Adoption

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The President:

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Foreword

"Big data", "data analytics", "information technologies", or "artificial intelligence" have become more than just buzzwords, they are an indispensable aspect of business practice and management theory. All too often, however, the same buzzwords are used without an accompanying in-depth analysis of their potential for practical application or possible obstacles. In addition, the question arises as to what extent theoretically conceivable applications are actually employed in practice. In his outstanding dissertation, Mr. Neumann addresses all of these questions by examining data analytics within the context of financial due diligence commonly performed during corporate transactions. This subject area is exceptionally compelling and is truly practice-relevant, as transaction advisors are expected to compile a comprehensive analysis of the asset, financial, and earnings positions of a target company within a very limited period of time. Consequently, financial due diligence as "the time-critical analysis of massive amounts of structured and unstructured data" is an ideal object of research. One could easily confine oneself and limit the research work, for example, to the development of theoretical possibilities for the use of big data and data analytics in the context of financial due diligence. However, Mr. Neumann rightly points out that "while […] the use dimension is essential for understanding the topic, the study of the adoption dimension is crucial to validate its practical relevance and derive recommendations for audit firms". "Use" and "adoption" are therefore directly related. It is precisely the connection between "use" and "adoption", and in the latter case the consideration of "organizational level" and "individual level", that makes this dissertation so novel and appealing.

With such a broad yet necessary research approach, it is evident that the dissertation generates a wide variety of results that will be of enormous interest to both scientists and practitioners. This is not least because Mr. Neumann has presented a work that is outstanding in both content and methodology. His work is an important contribution to the field and exemplifies the University of St. Gallen axiom – "From insight to impact". The stringency of the argumentation, the systematic approach of the structure, the visualization of the results, and the familiarity with the qualitative and quantitative methods used: all these are paradigmatic in every respect. Such an outstanding dissertation was written because Mr. Neumann was able to combine three things at the highest level: practical familiarity with the topic, theoretical competence in methodology, and a fluency with regard to the manifold relevant literature. This dissertation is highly recommended to all those interested in the future of financial due diligence and its further development.

Prof. Dr. Thomas Berndt

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The present work evolved during my educational leave of absence as an external doctoral student at the University of St. Gallen (HSG). In this preface, I would like to express my appreciation, thanks, and gratitude to the wonderful people that significantly supported my research.

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I would also like to express my appreciation to my fellow doctoral students, colleagues, and friends for their contributions to this thesis, the excellent cooperation in seminars, and the time spent together. In particular, I would like to mention my long-time friend Felix A. Hermes, with whom I had the opportunity to develop a joint research paper during my time in St. Gallen. I also owe special thanks to my colleague and friend Dr. Patrick Haslanger, with whom I have regularly critically reflected on our two dissertations.

My heartfelt thankfulness belongs to my family, my parents Annita A. and Franz-Josef Neumann together with my brother Daniel, and my partner in life, Hanna Weber, for being able to follow this path of life. Their continuous encouragement, support, and love throughout my academic studies and my professional life has always been unconditional. I was very delighted to be able to devote more time to them during my doctoral studies. This dissertation is dedicated to my loved ones.

Munich, March 27, 2020 Christopher Michael Neumann

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List of Abbreviations

A

AI	Artificial intelligence
API	Application programming interface
ASC	Accounting Standards Codification
AVE	Average variance extracted

B

BI	Business intelligence
BPM	Business performance management

C

CAATs	Computer-assisted audit techniques
Capex	Capital expenditures
CCC	Cash conversion cycle
CDD	Commercial due diligence
CLTV	Customer lifetime value
CMV	Common method variance
CoE	Center of excellence
c.p.	Ceteris paribus (all other things being equal)
CR	Composite reliability
C.R.	Critical ratio
CRM	Customer relationship management
C-TAM-TPB	Combined Technology Acceptance Model and Theory of Planned Behavior
CYT	Current year trading

D

DCF	Discounted cash flow
df	Degrees of freedom
DIO	Days inventory outstanding
DPO	Days payable outstanding
DSO	Days sales outstanding
DSS	Decision support systems
DTPB	Decomposed Theory of Planned Behavior

DWH	Data warehouse

E

EBIT	Earnings before interest and taxes
EBITDA	Earnings before interest, taxes, depreciation, and amortization
Ed.	Edition/Editor
Eds.	Editors
e.g.	Exemplī grātiā (for the sake of an example, for example)
EIS	Executive information systems
ELT	Extract, load, transform
ERP	Enterprise resource planning
esp.	Especially
et al.	Et alia/et alii/et aliae (and others)
ETL	Extract, transform, load
et seqq.	Et sequentia (and the following)
EUR	Euro

F

FCF	Free cash flow
FDD	Financial due diligence
FIFO	First-in, first-out
FIML	Full information maximum likelihood

G

GAAP	Generally accepted accounting principles
GPS	Global positioning system
GSANL	Germany, Switzerland, Austria, the Netherlands

H

HR	Human resources
HTMT	Heterotrait-monotrait ratio of correlations

I

i.a.	Inter alia (among other things, among others)
IAS	International Accounting Standards
IDT	Innovation Diffusion Theory

IFRS	International Financial Reporting Standards
IM	Information memorandum
incl.	Including
IoT	Internet of things
IP	Intellectual property
IPO	Initial public offering
IS	Information systems
IT	Information technology

L

LBO	Leveraged buy-out
LIFO	Last-in, first-out
LoI	Letter of intent

M

m	Million
M&A	Mergers and acquisitions
Max.	Maximum
Min.	Minimum
MIS	Management information systems
ML	Maximum likelihood
MM	Motivational Model
MPCU	Model of Personal Computer Utilization
MTMM	Monotrait-monomethod

N

NLP	Natural language processing
NoSQL	Not only structured query language

O

OLAP	Online analytical processing

P

p.	Page
Pot.	Potentially
pp.	Pages

PPE	Property, plant, and equipment
P&L	Profit and loss statement

R

RFID	Radio-frequency identification

S

SCT	Social Cognitive Theory
SEC	Securities and Exchange Commission
SEM	Structural equation model(-ing)
SKU	Stock keeping unit
SLOB	Slow-moving or obsolete inventory
SMEs	Small and medium-sized enterprises
S&P	Standard & Poor’s
SQL	Structured query language
SSC	Shared service center
Std.	Standard(-ized)

T

TAM	Technology Acceptance Model
TAM2	Technology Acceptance Model 2
TAM3	Technology Acceptance Model 3
TIB	Theory of Interpersonal Behavior
TOE	Technology-Organization-Environment Framework
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TTF	Task-Technology Fit Theory

U

Unstd.	Unstandardized
U.S.	United States (of America)
US-GAAP	United States Generally Accepted Accounting Principles
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2

V

VBA	Visual Basic for Applications
VDD	Vendor due diligence
vs.	Versus

W

WIP	Work in progress
WLAN	Wireless local area network
WPO	Wirtschaftsprüferordnung

Y

YTD	Year-to-date
YTG	Year-to-go

Special characters

>	Greater than
<	Less than
≤	Less than or equal to
|x|	Modulus of x

Abstract

Despite the contemporary relevance of technological advances in finance and accounting, today's literature is limited to four genealogies. This dissertation takes up the call for practice-oriented research and introduces a fifth, emerging research vein with respect to big data and data analytics: financial due diligence (FDD). In contrast to prior, mainly conceptual research, which lacks practical insights due to the sensitive nature of the topic, this thesis benefits from rare, first-hand data of the leading audit firms. The mixed methods research design, which combines expert interviews with a subsequent questionnaire, enables a comprehensive assessment of the (i) use and (ii) adoption of data analytics. This approach allows for an initial exploration of the use of data analytics along an FDD process framework, for deriving hypotheses on organizational and individual adoption based on the expansion of proven theoretical models, and for subsequently validating and generalizing of the findings.

The 20 expert interviews and the 333 questionnaire responses reveal significant changes in the FDD process. These process changes are due to the growing availability of financial, but also non-financial data, which depends on the initiator (sell-side/buy-side) and characteristics of the target firm. Changes in the FDD process are also the result of the increased reliance on data management and descriptive analytics solutions. The time-consuming steps necessary to build a comprehensive data model as the prerequisite for many analytics applications have led to a cost-benefit trade-off. Deal and target-related, project-related, and data-related factors must be weighed to determine whether the efficiency-related benefits of analytics justify the additional lead time required. Once applied, both non-financial (primarily target-internal) information and analytics are predominantly integrated into the commercially oriented profitability analyses. The long-term trend towards the use of predictive analytics and a more value-oriented approach initially necessitates exploiting the efficiency potential in the short term through higher adoption. Raising the adoption level requires an increase in demand, since a technology push by the Big Four, fueled by competitive pressure, can currently be observed. In addition, organizational determinants (e.g., degree of centralization) can have disparate effects in certain adoption phases. At the individual level, social influence, performance expectancy, and facilitating conditions have a significantly positive effect on adoption.

Zusammenfassung

Trotz der hohen Relevanz des technologischen Fortschritts für den Finanzbereich und das Rechnungswesen ist die heutige Literatur auf vier Genealogien limitiert. Diese Dissertation greift den Bedarf praxisorientierter Forschung auf und führt eine neue Forschungsrichtung im Kontext von Big Data und Data Analytics ein: Financial Due Diligence (FDD). Während der bisherigen, weitgehend konzeptionellen Forschung aufgrund der thematischen Sensibilität praktische Erkenntnisse verwehrt bleiben, profitiert diese Arbeit von den raren Primärdaten der führenden Wirtschaftsprüfungsgesellschaften. Das Mixed Methods Forschungsdesign, welches Experteninterviews mit einem Fragebogen kombiniert, ermöglicht eine umfassende Beurteilung der (i) Nutzung von Data Analytics anhand eines FDD-Prozessrahmens und (ii) Adoption anhand bewährter theoretischer Modelle. Dieser Ansatz erlaubt es, zunächst explorativ den Analytics-Einsatz zu untersuchen und Hypothesen über die Adoption herzuleiten, um die Erkenntnisse anschliessend zu validieren und zu generalisieren.

Die 20 Experteninterviews und die 333 Fragebogenrückmeldungen zeigen erhebliche Veränderungen im FDD-Prozess auf. Diese sind durch die wachsende Verfügbarkeit finanzieller, aber auch nicht-finanzieller Daten, welche vom Initiator (Sell-Side/Buy-Side) und den Merkmalen der Zielgesellschaft abhängen, begründet. Zudem sind die Prozessveränderungen auf den zunehmenden Einsatz von Datenmanagement- und deskriptiver Analytics-Software zurückzuführen. Insbesondere der zeitaufwändige Aufbau eines Datenmodells führt zu einer Kosten-Nutzen-Abwägung. Transaktions- und verkäufer-, projekt- und datenbezogene Faktoren werden abgewogen, um zu eruieren, ob die Effizienzvorteile von Analytics die zusätzlich benötigte Vorlaufzeit rechtfertigen. Nach der Anwendung werden nicht-finanzielle Informationen und Analytics-Software überwiegend in die Profitabilitätsanalysen integriert. Der langfristige Trend zum Einsatz von Predictive Analytics und einem stärker wertorientierten Ansatz setzt jedoch zunächst die Nutzung des Effizienzpotenzials durch eine höhere Adoption voraus. Dies erfordert eine Nachfragesteigerung, da die derzeitige Entwicklung einseitig von den Big Four vorangetrieben wird. Darüber hinaus können organisatorische Parameter (z.B. Zentralisierungsgrad) in bestimmten Adoptionsphasen unterschiedliche Auswirkungen haben. Auf der individuellen Ebene haben der soziale Einfluss anderer, Leistungserwartungen und begünstigende Bedingungen einen signifikant positiven Einfluss auf die Adoption.

1 Introduction

This introductory chapter provides an overview of the purpose, approach, and structure of this thesis. After an introduction to the contemporary relevance of research on the use of emerging technologies in finance and accounting (Section 1.1), gaps in prior research and the objectives pursued with this thesis are outlined (Section 1.2). Subsequently, the mixed methods research methodology is introduced (Section 1.3). The scope is described in order to delineate the boundaries and specify the perspective of this thesis (Section 1.4). Finally, the introductory chapter concludes with an outline of this thesis' structure (Section 1.5).

1.1 Motivation and background

The beginning of the 21st century heralds the onset of the so-called information age[1], which marks the rapid shift from traditional industry to an information technology (IT)-based economy. The vast increase in digital information, paired with technological advancements, affects many business models and the inherent business practices.[2] Certainly, this change includes finance and accounting processes. Bhimani and Willcocks (2014) substantiate this view stating that "[t]he finance function is being deeply affected by the advent of digital technologies" (p. 470). The impact on individual activities that characterize job profiles in finance and accounting is enormous. For example, Frey and Osborne (2017) report that the current activities of accountants and auditors can be automated within the next one to two decades with a probability of 94%.

For the last five years, research in these domains has increasingly addressed the impact of technological change.[3] Most studies focus on the topics *big data* and *analytics*, which, according to Griffin and Wright (2015), "permeate almost all aspects of major companies' decision making and business strategies" (p. 377). According to Gepp,

[1] This term is synonymous with computer age, digital age, and new media age.

[2] Besides finance, Holsapple, Lee-Post, and Pakath (2014) mention such as examples as "marketing, human resources, business strategy, organization behavior, operations, supply chain systems, information systems" (p. 132). However, this dissertation focuses on analytics applications in the finance and accounting domain (see Section 3.1.2.2).

[3] References to the term big data emerge in finance and accounting literature around 2011 (Cockcroft and Russell, 2018). Alles and Gray (2016) observe a sharp increase in presentations and publications on big data by accounting academics and practitioners since 2015.

Linnenluecke, O'Neill, and Smith (2018), related research in the finance and accounting domain concentrates on four main genealogies: auditing and "financial distress modelling, financial fraud modelling, and stock market prediction and quantitative modelling" (p. 102).

This dissertation expands existing research with a fifth, emerging research vein with respect to big data and data analytics: financial due diligence (FDD) as a core part of the mergers and acquisitions (M&A) process.[4,5] Feix (2019) and Feix and Popp (2018) introduce the topic of digitalization across the entire deal cycle. They thereby highlight FDD and characterize it as prime for the use of analytics. They expect the use of corresponding technologies to solve the main challenge of due diligences: the time-critical analysis of massive amounts of structured and unstructured data.[6] Moreover, Earley (2015) poses the question as to "whether the core business of public accounting – that is, auditing – will benefit from an investment in DA [data analytics] capabilities or whether DA is ultimately more in the domain of consulting" (p. 494), to which M&A advisory also belongs. She thus indicates that advisory is likely to benefit more strongly from the use of analytics. Beyond voices from academia, M&A practitioners have also claimed that FDD benefits greatly from the use of data analytics. For example, Rauner (2019), a partner at Deloitte, describes current use cases for analytics software in the FDD process. He thereby highlights such key advantages as greater process speed and efficiency, increased standardization, higher data quality and transparency, opportunities to conduct new analyses, and, finally, deeper insights. In addition to these aspects, Beckmann et al. (2019) praise the increased flexibility of analyses through data analytics tools in FDD that enables consultants to quickly react to ad hoc requests from their clients.[7] Finally, a study by Merrill Corp. (2018) among investors and M&A advisors confirms the expected acceleration of the due diligence process through the use of data analytics technology. Based on the great

[4] Although numerous academic publications exist that deal with the M&A process and its components, the impact of digitalization has not been in focus of research thus far (see Section 1.2).

[5] FDD is not only a core part of the M&A process. It also is the most frequently applied functional form of due diligence. In their empirical analysis for the German market, Marten and Köhler (1999) find that an FDD is conducted in 94% of the investigated M&A transactions, respectively. In a more recent investigation, Berens and Strauch (2011) even report a rate of 94.7% (see Section 2.2.3.1).

[6] Feix and Popp (2018) project "gains in efficiency, quality, and speed, and thereby competitive advantages in due diligence processes" [translated from German] (p. 282).

[7] The article section related to data analytics in FDD is written by Mickerts and Ganzen of the Next Ten firm Warth & Klein Grant Thornton.

potential of using analytics and the choice of an appropriate scope that allows for sufficient depth, this work focuses on FDD, a key component of the M&A process.

1.2 Research gap and objective

While there is a vast body of literature that deals respectively with the M&A and due diligence processes and their different phases, the impact of modern technologies has thus far been neglected. With the exception of a few, but barely noticed, studies that address the transition from physical to virtual data rooms (e.g., Kummer and Sliskovic, 2007; Timson, 2015), literature on the technological advancement of the M&A process in general, and the due diligence process in particular, is scarce. With the exception of the articles by Rauner (2019) and Beckmann et al. (2019), which deal with the use of database software in FDD and selected benefits from data analytics in FDD, respectively, the author is not aware of any studies on the use of modern technologies in due diligence. From the author's point of view, there are three underlying reasons for this. First, the M&A topic is highly sensitive for the companies involved, which makes practice-oriented research (e.g., in the context of case studies) difficult. Second, the market for M&A services, in particular FDD, is small and dominated by a few providers (see Section 2.2.3.4). For these providers, especially in Europe, the digital transformation of existing processes represents an emerging and highly sensitive field about which they tend not to share any information (e.g., with researchers). Consequently, a "lack of information being provided by public accounting firms about their approaches to DA" (Earley, 2015, p. 494) is evident. In the context of this research, interview partners and questionnaire participants could only be obtained with a prior guarantee of anonymity. Third, and building on this argument, many contributions in process-oriented M&A and due diligence research originate from practitioners, which presents unique problems. On the one hand, practitioners try not to disclose sensitive information, which would allow readers to draw inferences about their employer. On the other hand, due to the lack of established standards, the contributions of practitioners do not allow for conclusions to be drawn about cross-company applicability.

The observation that little prior research in data analytics has been done can be extended, albeit to a lesser extent, to finance and accounting in general. For instance, Payne (2014) notes that "surprisingly few accounting academics [are] researching big data and analytics" (p. 495). Arnaboldi, Busco, and Cuganesan (2017) concur and note that despite the topic's practical relevance as seen through "anecdotal evidence and case studies" (p. 763), empirical investigation in this field is still in its infancy. Moreover, most technology-related research in the accounting field exhibits a conceptual or normative character (e.g., Brown-Liburd, Issa, and Lombardi, 2015; Cao, Chychyla, and Stewart, 2015) with "little being known about how developments affect the actual practice" (Salijeni, Samsonova-Taddei, and Turley, 2019, p. 2).[8]

These observations concerning the orientation of previous research also hold true for the few studies that deal with the use of technology in due diligence.[9] For example, Feix (2019) and Feix and Popp (2018) provide a summary of digitalization as it pertains to financial, legal, and compliance due diligence, but without offering practical insights – although the authors do admit that the Big Four firms[10] run numerous projects related to the digital transformation of their due diligence services. Analogous to other researchers, they remain on the conceptual level and do not provide evidence for the actual use and adoption of data analytics in practice.

Consequently, Appelbaum, Kogan, and Vasarhelyi (2017) point out that "[r]esearch is needed on modern analytics methods to establish their applicability in different instances" (p. 10). Earley (2015) mentions that "[s]ervice organizations, such as public accounting firms, are in the race to provide better and more comprehensive DA [data analytics] services to their clients, but the question still remains as to how they will actually accomplish this" (p. 494). She thereby underscores the need for research that considers the actual use and adoption of analytics. Despite calls for investigations on the use of big data for accounting purposes (Vasarhelyi, Kogan, and Tuttle, 2015), as well as different use cases of different data analytics techniques (for the auditing domain see e.g., Appelbaum et al., 2017; Appelbaum et al., 2018; Salijeni et al., 2019) and their critical[11] adoption (Dagiliene and Kloviene, 2019; Janvrin et al., 2008; Kokina and Davenport, 2017), research in these areas is scant.

[8] A significant portion of these normative studies cannot be absolved from remaining vague in their assertions and not sufficiently defining technology-related terms. Earley (2015) states that "many of these [articles] are thought pieces" (p. 494).

[9] Besides aspects that hold true for all finance and accounting domains, the scant previous literature in the due diligence field may well be attributable to the late integration of due diligence research into business research in Europe (Grote, 2007).

[10] The Big Four are the four biggest professional services networks in the world: Deloitte, EY, KPMG, and PwC. They offer services in the areas of audit, assurance, taxation, consulting, advisory, actuarial valuation, corporate finance, and legal advice.

[11] Harder (2018) points out adoption's criticality for the subsequent technology use stating that "data analytics can fail due to a lack of user acceptance" (p. 1482).

Evidence from research on the use and adoption of big data and data analytics could be particularly valuable for multiple reasons. First, it helps the research community to understand how large professional service firms use certain technologies in the as yet underexamined due diligence process. Thereby, analytics is regarded in conjunction with the data processed and analyzed (e.g., internal and external as well as financial and non-financial data) to account for interdependencies between data sets used and data analytics techniques employed. Second, it enables comparing both the technology adoption behavior itself and the impact of underlying causes on that adoption behavior for the other service offerings of large accounting firms.[12] Kokina and Davenport (2017) assert that the most crucial evidence for a technology's relevance to accounting is its adoption by practicing accountants and auditors. Third, knowledge gained can be transferred back to related research veins and create new research questions in these domains. Fourth, the results can serve as a benchmark for practitioners to evaluate their companies' adoption of data analytics and associated usage efforts (Janvrin, Bierstaker, and Lowe, 2008). Moreover, practitioners can gather and subsequently incorporate innovative ideas about analytics in their companies (Appelbaum, Kogan, and Vasarhelyi, 2018). Finally, the findings related to the critical adoption factors can be employed as guidelines by practitioners to promote the use of data analytics in their organizations (Janvrin et al., 2008; Lowe, Bierstaker, Janvrin, and Jenkins, 2017).

For these reasons, this thesis investigates both the use of big data and analytics and the adoption of data analytics. While the study of the use dimension is essential for understanding the topic, the study of the adoption dimension is crucial to validate its practical relevance and derive recommendations for audit firms. This thesis strives to answer the following overarching research questions in this evolving research vein:

Use of big data and data analytics

1. To what extent and how do audit firms *integrate big data* in the FDD process?
2. How do audit firms *use data analytics* along the FDD process?

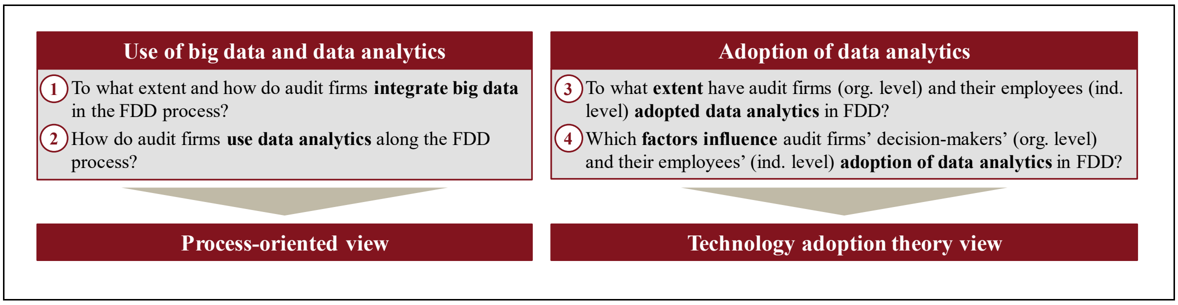
[12] For instance, Alles and Gray (2016) suggest combining external audit research with research outside this domain and particularly mention public accounting firm activities. Salijeni et al. (2019) explain that "given the scale of the investment required in the process of developing and maintaining BDA [big data analytics] algorithms, software and tools […] the auditor will, as a result, end up using analytical tools which have been created to serve the needs of the firms' other service lines." (p. 114)

Adoption of data analytics

3. To what *extent* have audit firms (organizational level) and their employees (individual level) *adopted data analytics* in FDD?
4. Which *factors influence* audit firms' decision-makers' (organizational level) and their employees' (individual level) *adoption of data analytics* in FDD?

The first two research questions concerning the use of big data and data analytics in FDD are considered from a *process-oriented view* as the conceptual framework. The latter two research questions are regarded from a *technology adoption theory view* as the theoretical framework (see Figure 1.1).

Figure 1.1: Research questions and conceptual/theoretical frameworks



Source: Own illustration

1.3 Research methodology

This thesis builds on existing theoretical literature in the areas of due diligence, big data and data analytics, and technology adoption. Besides this theory-based perspective, the introduction of the new, fifth genealogy will benefit from the review of existing research, particularly in the auditing field. Although the due diligence process is less structured, less regulated, and has a stronger forward-looking, value-oriented perspective than auditing, many overlaps exist. Extensive study of adjacent literature streams helps frame and structure the subsequent empirical analysis and helps transfer knowledge from other finance and accounting disciplines to FDD. Inspired by Kokina and Davenport's (2017) procedure in the auditing field, the FDD process will be broken out into its different stages (preparation, analysis, reporting). The core phase – the analysis – is split according to its review foci (profitability analysis, balance sheet analysis, cash flow analysis, business plan validation). This process-oriented view structures the subsequent empirical research. Similarly, established technology adoption models support the examination of adoption in the technological (analytics) and contextual (FDD) environment under investigation. Significantly, in contrast to prior studies, this study applies technology acceptance theories to both the individual and the organizational levels. In doing so, this thesis resolves the shortcoming of previous studies that did not take into account both the firms' decisions to offer certain technologies (organizational level) and the subsequent adoption of those technologies by their employees (individual level) (see Section 4.1.1).

The empirical approach of this dissertation follows a mixed methods research design. This methodological pluralism integrates quantitative and qualitative methods for two main reasons: first, to overcome the individual weaknesses of these two methodologies and second, to answer research questions that do not only call for quantification but also require an interpretative understanding of the research problem (Johnson and Onwuegbuzie, 2004). In particular, when "it is necessary to draw on multiple data sources to understand complex phenomena" (Bazeley, 2008, p. 134), a mixed methods approach can enhance the depth and breadth of the results (Jogulu and Pansiri, 2011). This thesis' research design follows i.a. the recommendations made by Alles and Gray (2016) who, on the one hand, predict that most near-term research in the field at hand will be qualitative in nature (see also Gepp et al., 2018) and, on the other hand, seek out the rare opportunities for quantitative research.[13]

In this thesis, this approach benefits from three common purposes of mixed methods: triangulation, expansion, and development. Triangulation is the convergence of findings from multiple sources in order to strengthen their validity (Schirmer, 2009; Wrona and Wappel, 2010). Expansion extends the depth and breadth of the research subject (Johnson and Onwuegbuzie, 2004). Development means that one method (here: qualitative interviews) makes it possible to conduct further research with another method (here: quantitative questionnaire) (Greene, Caracelli, and Graham, 1989).

The mixed methods design follows a sequential chronology (Johnson and Onwuegbuzie, 2004; Kuß, 2010; Wrona and Wappel, 2010). The first method employed is qualitative, semi-structured expert interviews (Meuser and Nagel, 1991; Meuser and

[13] Alles and Gray (2016) explain that "[b]ecause of the newness of these activities at the accounting firms there is likely to be a lack of quantitative data in the immediate future" (p. 57). Nonetheless, the mixed methods approach has already been field-tested at the intersection of accounting and technology. For example, Omoteso, Patel, and Scott (2010) have applied a combination of one-on-one interviews and questionnaires.

Nagel, 2009; Raithel, 2008). Being the first to examine the links between data analytics and FDD, the interviews have a primarily explorative character.[14] The first interviews are held with leading due diligence practitioners working for the large accounting firms that possess substantial knowledge of, and experience with, data analytics. These practitioners come from the author's professional network. After the initial interviews, a snowballing approach supports the development of a network of contacts with relevant knowledge and experience.[15] The insights from both prior studies and expert interviews are used in an inductive way to describe general characteristics of the use of big data and data analytics; existing considerations from adoption theory are validated and expanded. Finally, the qualitative analysis serves as a basis for deriving sound hypotheses with regard to adoption (Hussy, Schreier, and Echterhoff, 2010; Schirmer, 2009).

In a second empirical part, the insights into big data and analytics usage in FDD are substantiated and the previously developed hypotheses are validated with the help of a quantitative research method: the questionnaire as survey instrument, which has already been applied to related topics (e.g., Lowe et al., 2017). In a deductive way, the questionnaire supports the validation and generalization of previously gained knowledge on a large number of cases (Bortz and Döring, 2006; Hussy et al., 2010). Moreover, testing technology adoption theories commonly requires a sufficient number of data points that cannot be met with interviews alone. However, it should be noted that the required sample size in this study can be achieved on an individual level (unit of analysis: individual employees), but not on an organizational level (unit of analysis: companies). The focus on the highly concentrated industry of FDD service providers (see Section 2.2.3.4) does not allow sufficient data to be collected in order to draw statistically robust conclusions from quantitative research models. Therefore, the organizational perspective is examined in qualitative research, whereas the individual view is investigated in both the qualitative and quantitative, survey-based research (see Figure 1.2). The analysis of the questionnaire data on individual technology adoption is performed using a covariance-based structural equation model (SEM). Moreover, a multi-group analysis is conducted to investigate not only the main effects but also possible interaction effects.

[14] Analogously, Al-Htaybat and von Alberti-Alhtaybat (2017) who were the first to investigate the links between big data and corporate reporting use a qualitative analysis with an interpretative view of 32 interviews.

[15] Salijeni et al. (2019), for instance, selected a comparable approach in the auditing domain.

Figure 1.2: Validation of organizational and individual adoption

	Theory	Adjacent literature	Qualitative analysis (expert interviews)	Quantitative analysis (questionnaire)
Organizational adoption (TOE)	✓	✓	✓	✗
Individual adoption (UTAUT)	✓	✓	✓	✓

✓ Considered/validated in this dissertation ✗ Not considered/validated in this dissertation

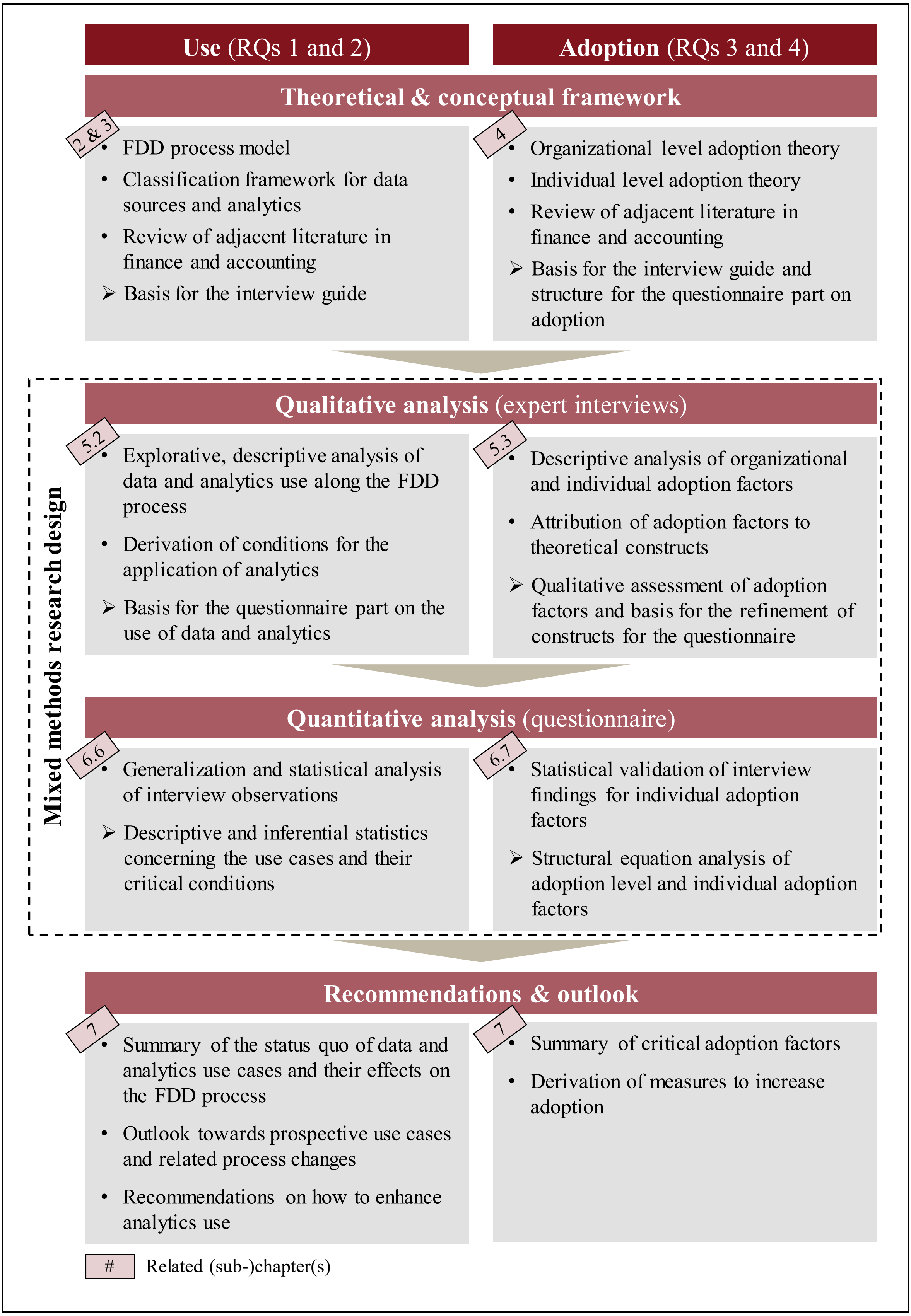
Source: Own illustration

Due to the continuing evolution of the use of data analytics, the present study employs a cross-sectional research design (Bryman, 2006). Carrying out the data collection process in a consistent environment is essential for appropriately measuring the variability of technology use and adoption across organizations and individuals.

Following the "call for more research and a greater alignment to practice" (Gepp et al., 2018, p. 102) (see also Janvrin and Wood, 2016; Kokina and Davenport, 2017), the approach in this thesis greatly benefits from the strong use of practitioners' expert knowledge in both the qualitative and the quantitative components. First and foremost, such first-hand data from the largest accounting firms is very rare since these firms and their employees commonly tend not to disclose sensitive information (see Section 1.2). This first-hand data makes it possible to provide practical examples of the data analyzed and the methods and technologies utilized in each stage of the FDD process. Second, in practice, sellers and buyers only rely on internal teams to carry out due diligence for low complexity transactions (Kappler, 2005). Instead, they involve external parties such as – for FDD – audit firms for the majority of transactions (Grote, 2007). Consequently, the transaction advisors' experience and knowledge particularly qualify them to provide insights as part of this dissertation. Moreover, the interviewed and surveyed reference group – in its role as external service provider – is forced to balance the (technology-related) feasibility side and the necessity side (Issa, Sun, and Vasarhelyi, 2016).

Figure 1.3 illustrates the different elements of the research approach and their interrelations.

Figure 1.3: Research design of this thesis



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1.4 Scope

In the following section, the scope of this thesis is defined to ensure a transparent delineation and an adequate treatment of the research questions.

Research that combines aspects of digitalization and the M&A process can be classified as following either the *content view* or the *processual view* (Feix, 2018). The content view focuses on the impact of digital business models in high-tech and traditional industries on the M&A process. In contrast, this thesis covers the processual view. The process and tool-related perspective analyzes how digital instruments can be used to implement M&A processes faster, more efficiently, and with higher quality (Feix, 2018).

Within the M&A process, the functional focus lies on FDD for three reasons. First, FDD has notable similarities with areas for which the use of data analytics has already been partly examined (e.g., auditing, financial fraud modeling). Thus, previous research findings may be tested as part of the expert interviews within this thesis. Second, due to its structural, analysis-driven nature, FDD is prime for the use of analytics (Feix, 2019; Feix and Popp, 2018). Third and finally, anecdotal evidence suggests that FDD – together with valuation – is the leading field for the use of analytics in transaction advisory. It therefore represents a highly practice-relevant research field.

The technological focus lies on data analytics. The vast majority of technology-related studies dealing with finance and accounting processes focus on the use of data analytics, which underlines its importance in these fields. The application of analytics technologies cannot be examined without an understanding of the data that is analyzed within such processes (Alles and Gray, 2016; Ruhnke, 2019). Therefore, this thesis also aims to capture the complexity of the data used. Concretely, it examines how the analysis of traditional finance and accounting data[16] has evolved and to what extent non-financial information from both target-internal and target-external sources (especially big data) is already integrated into FDD.

Lastly, this thesis examines the use of data analytics from the perspective of audit firms, which commonly carry out FDD projects (Grote, 2007; Pomp, 2015). In their

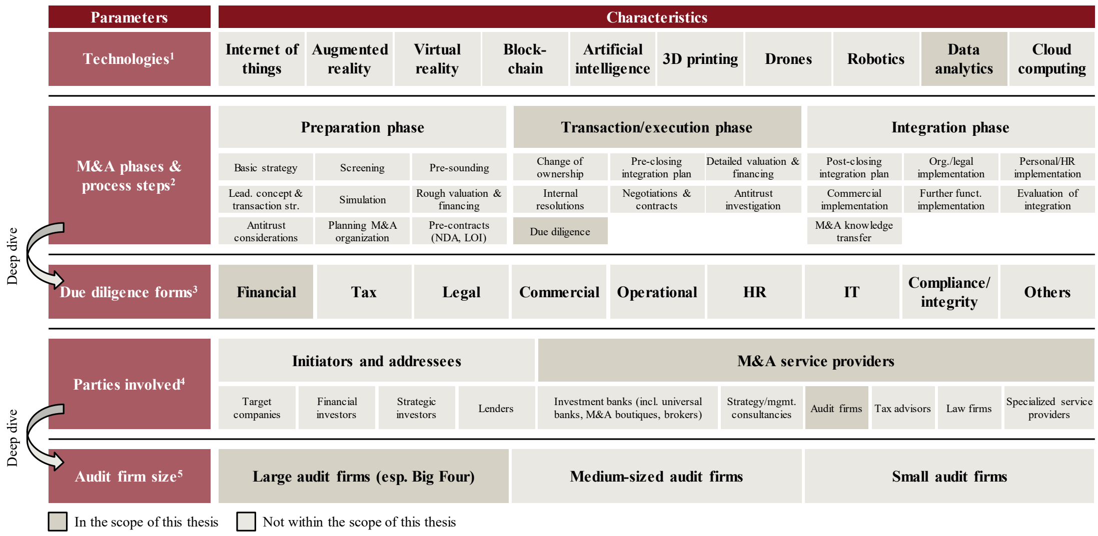
[16] The checklist by Pomp (2015) provides an overview of information traditionally requested in an FDD process.

position as service providers, they are forced to take into account not only their own interests but must also consider their clients' (target, potential acquirers, and potential lenders) needs. In summary, this focus still allows for a balanced view of the supply and demand of analytics-based services.

In line with prior research, this dissertation mainly focuses on large accounting firms, especially the Big Four (Janvrin et al., 2008; Omoteso et al., 2010). For instance, Janvrin et al. (2008) write that "[t]he limited amount of research related to auditors' use of IT has primarily focused on the impact of IT in large audit firms" (p. 4). It follows that a different focus could limit the transferability of previous results. Besides their dominance (and thus, representativeness for a substantial share of the market) (see Section 2.2.3.4), this prior focus may be best explained with the greater openness towards the use and adoption of larger audit firms in general, and the Big Four in particular (Omoteso et al., 2010), which has been empirically proven in various studies (Janvrin et al., 2008; Lowe et al., 2017; Rosli, Yeow, and Siew, 2013). Overall, focusing on larger audit firms enables gaining more insights into the possible use of analytics in FDD.

The different elements that characterize the scope of this thesis are illustrated in the morphological box in Figure 1.4.

Figure 1.4: Scope of this thesis



Notes:

1) The first eight technologies illustrated are the so-called Essential Eight, the most pertinent technologies selected by PwC from more than 150 discrete technologies based on business impact and commercial viability over the next five to seven years. The latter technologies are already more established, yet (potentially) relevant for the M&A process.

2) See Borowicz (2006) and Lucks and Meckl (2015).

3) See Pomp (2015).

4) See Lucks and Meckl (2015) and Pomp (2015).

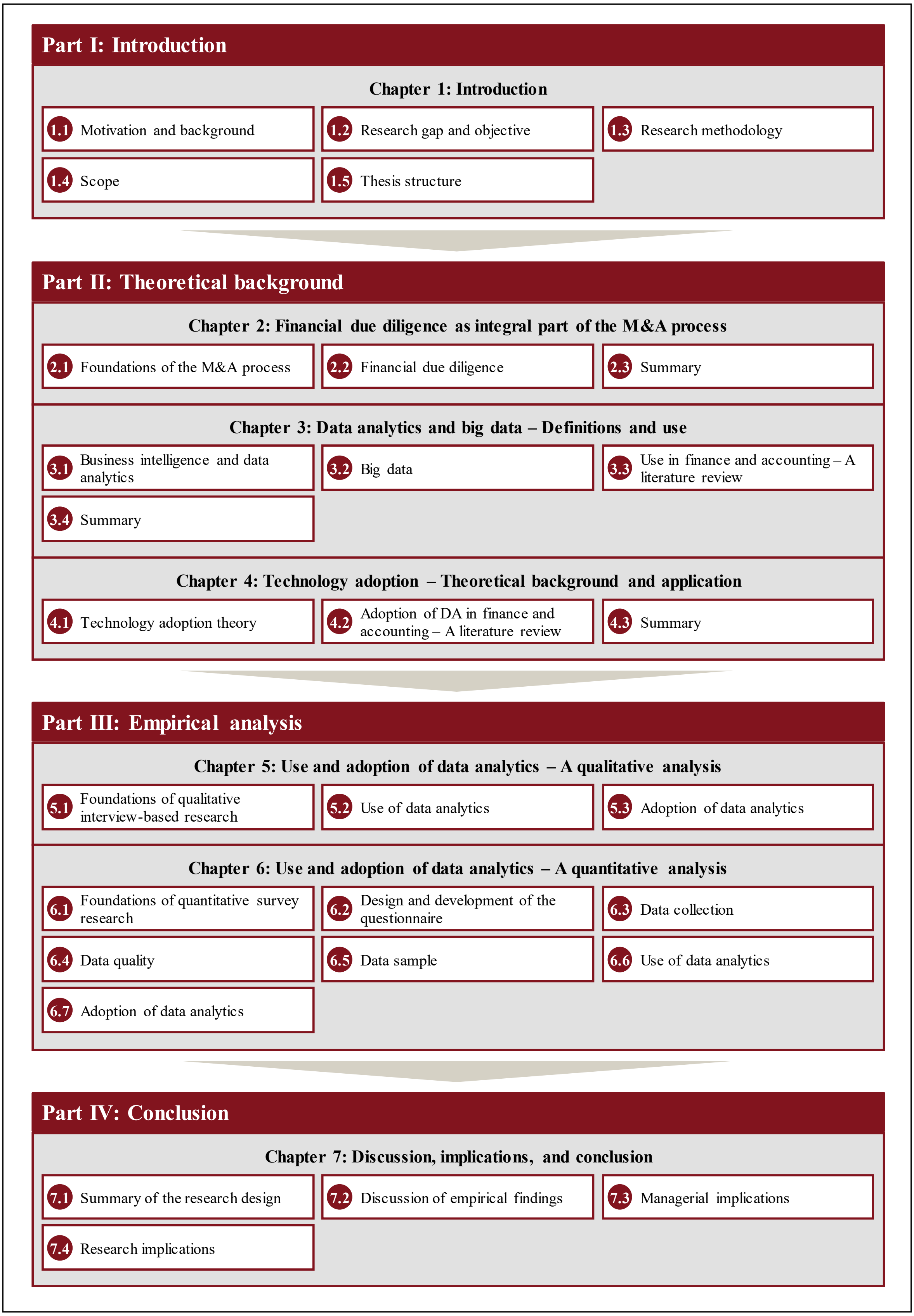
5) Based on the revenue data provided by Köhler and Ratzinger-Sakel (2019), there are 14 large audit firms (net turnover >40m EUR) and at least 16 medium-sized audit firms (net turnover >8m EUR) in Germany (according to the net turnover measure and irrespective of the further two criteria, total assets and number of employees, as outlined in Article 3 II-IV of the Directive 2013/34/EU).

Source: Own illustration

1.5 Thesis structure

This dissertation is comprised of four main parts. Part I introduces preliminary elaborations and lays out the foundation for this study (Chapter 1). Part II contains the theoretical background and literature review (Chapters 2-4). It is divided as follows: The second chapter explains key M&A concepts, provides a process structure for FDD, and identifies processual improvements through the use of analytics. The third chapter presents the theoretical basis for the topics of big data and data analytics and illustrates their current use in the finance and accounting domain. The fourth chapter introduces different adoption theories and previous technology adoption research on audit firms. Part III of this thesis, the empirical analysis, presents the interpretative interview-based analysis (Chapter 5) and the quantitative survey-based research (Chapter 6) of the use and adoption of data analytics in FDD. In this part, insights are generated and hypotheses are developed from expert interviews, which are subsequently validated with the help of a questionnaire. Part IV contains the concluding remarks (Chapter 7) that summarize the results, explain theoretical and practical implications, discuss the limitations of the study, and provide an outlook for future research possibilities. Figure 1.5 illustrates this structure.

Figure 1.5: Structure of this thesis



Source: Own illustration

2 Financial due diligence as integral part of M&A

This second chapter begins with an overview of M&A and includes the description of a generic M&A process (Section 2.1). FDD and its integrated role in the M&A process are then introduced. It is important to note that prior research on the FDD process either lacks completeness or a sufficient level of detail. Consequently, existing literature is combined to give a detailed presentation of the entire FDD process. The objectives of FDD, which have thus far only been unsystematically and incompletely described in various studies, are bundled in this dissertation. Finally, the potential for improvement in the achievement of these goals by means of analytics technology is examined (Section 2.2). The chapter closes with a brief summary (Section 2.3).

2.1 Foundations of the M&A process

This section presents the fundamentals of M&A. After a short definition and classification of different forms of M&A (Section 2.1.1) and a characterization of relevant stakeholders (Section 2.1.2), motives are categorized and outlined with examples (Section 2.1.3), and the historical success is evaluated (Section 2.1.4). Finally, the M&A process is described in a generic form in order to allow for a definition of the role of FDD, which is discussed in Section 2.2, in this process (Section 2.1.5).

2.1.1 Definition and classification of M&A

The following definition and classification serve to create a uniform understanding of M&A and to delimit the forms dealt with in the context of this thesis.

2.1.1.1 Definition of M&A

Since the first wave of takeovers at the end of the 19th century, the term M&A, originating in the Anglo-American region, has been widely used (Wirtz, 2017). Lucks and Meckl (2015) define M&A as “all transactions that are related to the acquisition or sale of companies or parts of companies” [translated from German] (p. 5) and consider the change in the ownership structure of the equity to be a constitutive feature.[17] In addition, they differentiate mergers from acquisitions. Mergers are combinations of two or more legally and economically independent companies, whereby at least one of the companies involved loses its legal independence (through integration or

[17] For an overview and discussion of further definitions of M&A, see Horzella (2009).

the creation of a new organization). Acquisitions are defined as purchases of companies or parts of companies either through the transfer of company shares (share deal) or through the transfer of all or certain parts of a company's assets and liabilities (asset deal) or through a combination of both. Accordingly, acquisitions restrict or completely abandon economic independence, while legal independence can be maintained (Lucks and Meckl, 2015). As with Lucks and Meckl (2015), however, the separation of the terms mergers and acquisitions will not be dealt with in detail in the following. In addition, the complete takeover of the target company is assumed and minority interests will not be dealt with separately.

2.1.1.2 Classification of M&A

Besides defining the terminology, the characteristics of M&A can be well explained based on systemization criteria. In addition to the distinctions between mergers and acquisitions and between an asset deal and a share deal mentioned above, corporate transactions can be classified on the basis of further dimensions (see Figure 2.1).[18]

Figure 2.1: Classification of M&A

<table>
<tr><th>Parameters</th><th colspan="30">Characteristics</th></tr>
<tr><td>Relation to the company's lifecycle</td><td colspan="6">New foundation/ refounding</td><td colspan="6">Strategic transformation</td><td colspan="6">Restructuring/ reorganization</td><td colspan="6">Sale/ demergers</td><td colspan="6">Liquidation</td></tr>
<tr><td>Investment type</td><td colspan="10">Cooperation</td><td colspan="10">Merger</td><td colspan="10">Acquisition</td></tr>
<tr><td>Intervention on legal/ economic independence</td><td colspan="6">No stake in the equity</td><td colspan="6">Minority</td><td colspan="6">Parity</td><td colspan="6">Majority</td><td colspan="6">Complete acquisition</td></tr>
<tr><td>Integration of the value chain</td><td colspan="10">Horizontal</td><td colspan="10">Vertical</td><td colspan="10">Conglomerate/lateral</td></tr>
<tr><td>Method of payment</td><td colspan="15">Asset deal</td><td colspan="15">Share deal</td></tr>
<tr><td>Form of financing</td><td colspan="15">Equity financing</td><td colspan="15">Debt financing</td></tr>
<tr><td>Assessment by the target firm's management</td><td colspan="15">Friendly takeover</td><td colspan="15">Hostile takeover</td></tr>
</table>

Source: Own illustration based on Horzella (2009)

[18] For a detailed description of the various facets of M&A, refer to Horzella (2009).

2.1.2 Characterization of stakeholders involved

In order to understand the different perspectives on corporate transactions and their implications for the M&A process, acquirers, sellers, and selected external M&A service providers are described below.[19]

2.1.2.1 Acquirers

First, the two most typical groups of investors in corporate transactions, industrial buyers (so-called strategic acquirers) and financial investors, are distinguished.[20]

Strategic acquirers

The majority of acquisitions are attributable to strategic acquirers (Lucks and Meckl, 2015). They acquire companies in their own or another industry, mostly for strategic reasons (e.g., expansion or diversification of business activities) and with a long-term investment horizon (Hinne, 2008; Lucks and Meckl, 2015; Pomp, 2015; Störk and Hummitzsch, 2017). Accordingly, the assessment of the target prior to the acquisition focuses primarily on the evaluation of strategic aspects, the profitability situation, and synergy potentials (Pomp, 2015; Störk and Hummitzsch, 2017). Financing aspects (Störk and Hummitzsch, 2017) and an exit strategy with the maximum net return (Lucks and Meckl, 2015) normally play a subordinate role.

Financial investors

In the context of M&A, the financial investors group is mainly comprised of private equity companies (Lucks and Meckl, 2015). In the following, particular reference is made to buy-outs (in contrast to venture capital such as seed capital or early and late stage capital), as the business model of this type is based on M&A as an instrument (Lucks and Meckl, 2015). Their investment is short to medium-term and is characterized by a clear exit strategy from the outset with the aim of achieving the highest possible return (Lucks and Meckl, 2015; Störk and Hummitzsch, 2017). Often, a large proportion of these transactions are debt financed in order to benefit from the leverage effect (so-called leveraged buy-out (LBO)) (Störk and Hummitzsch, 2017). Consequently, the operating and free cash flows as well as net working capital, including

[19] Participants within these three groups are not considered, nor are other parties directly or indirectly involved (e.g., competitors, suppliers, customers, public institutions, and trade unions). A detailed description of these stakeholders can be found in Lucks and Meckl (2015).

[20] For an overview of a third acquirer group, the target companies' management in the context of so-called management buy-outs, refer to Lucks and Meckl (2015).

seasonality, are of utmost importance for financial investors (Bredy and Strack, 2011).

Simplistically, the LBO-based business model can be summarized in four stages: (i) funding, (ii) acquisition of the target, (iii) value creation, and (iv) exit (Lucks and Meckl, 2015). In the (i) funding phase, a fund is established and large investors (e.g., pension funds, insurance providers, companies, family offices) are persuaded to acquire shares of the fund. After the identification of a target company, debt capital of various risk classes is raised in large quantities (Lucks and Meckl, 2015). In the (ii) acquisition of target companies, the focus is on identifying companies with stable cash flows to repay the high level of debt (Lucks and Meckl, 2015; Störk and Hummitzsch, 2017) and with inherent value appreciation potential, since unlike strategic buyers, no synergy potential[21] is likely to be realized (Lucks and Meckl, 2015). These differences, when compared to strategic investors, are also reflected in the M&A process. For instance, in order to compensate for the often less detailed knowledge of the market and the competitive situation compared to strategic investors, financial investors conduct a higher proportion of commercial due diligence (CDD) (Bredy and Strack, 2011; Pomp, 2015). After completing the transaction, there are three levers available for (iii) value creation: strategic measures (e.g., repositioning, geographical expansion), operational measures (e.g., efficiency improvements), and financial engineering (Lucks and Meckl, 2015). As part of the (iv) exit strategy, which has already been defined at an early stage, the company is eventually resold after around three to seven years (Pomp, 2015) to either strategic investors or other financial investors. Another exit option is an initial public offering (IPO) (Lucks and Meckl, 2015).

2.1.2.2 Sellers

It is necessary to distinguish among the types of sellers, which include private equity companies who become sellers as part of their exit strategy (see Section 2.1.2.1), private sellers, and state sellers (Hinne, 2008). State sellers primarily arise through the privatization of infrastructure and services previously provided under public law. In the past, for example, telecommunications, gas, water and electricity supply,

[21] Although value must typically be created on an inherent, standalone basis in LBOs, synergy effects play a crucial role in the context of buy-and-build strategies, which are characterized by add-on acquisitions (Brigl, Hammer, Hinrichs, Jansen, and Schwetzler, 2018; Pomp, 2015).

transport and logistics, and the healthcare sector were strongly affected by such transactions (Hinne, 2008). With private sellers, a distinction is made between large private companies and owner-managed, mostly medium-sized companies. In addition to the wide range of superordinate motives (e.g., sale due to antitrust conditions, adaptation to changed corporate strategy, focus on core competencies, gain in management and control through lower diversification, buy-operate-sell strategy, defense against hostile takeovers, and liquidity constraints), the lack of family succession often plays a central role for owner-managed companies when deciding to sell (Duhaime and Grant, 1984; Hinne, 2008).

2.1.2.3 External service providers

In order to cope with the often complex, multi-layered, interdisciplinary, and cross-sector situations in M&A transactions, acquirers and sellers usually engage external M&A service providers (Hinne, 2008). With the help of the service providers, they ensure that the different know-how required in the M&A process is made available at short notice in high quality and quantity. As a third party, the consultants guarantee independence, neutrality, and objectivity. In addition, companies without their own M&A department can, in particular, bridge capacity bottlenecks with the help of service providers (Hinne, 2008).

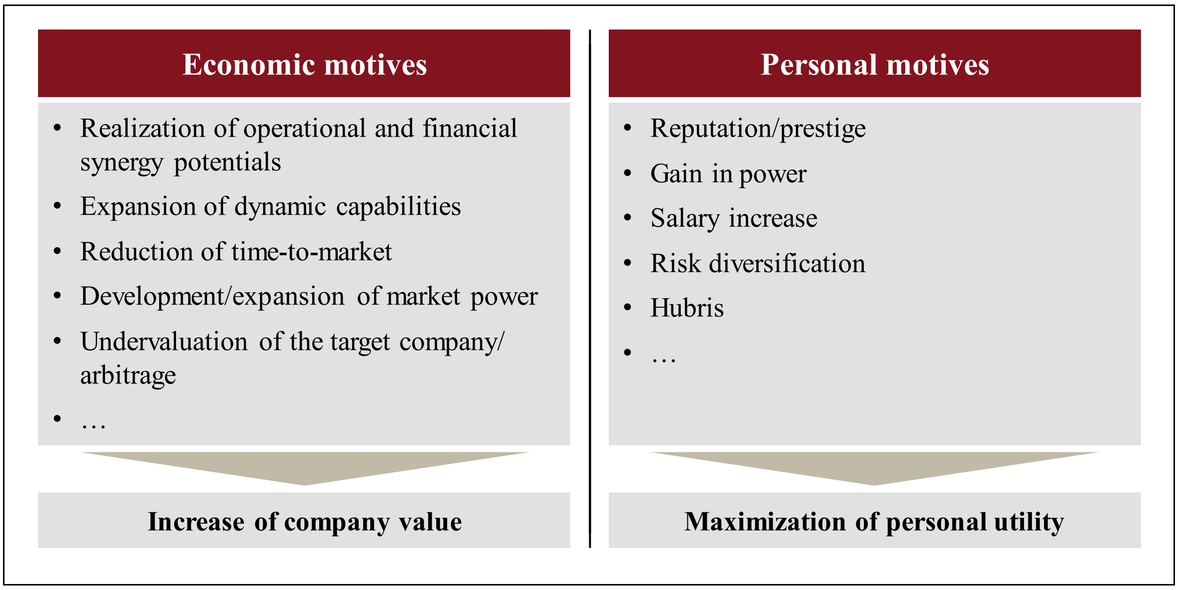
The external M&A service providers are usually differentiated according to their process coverage. As full-service providers, investment banks, M&A boutiques, and management consultancies (as well as leading law firms and audit firms) cover all phases of an M&A transaction. Conversely, the majority of lawyers, auditors, tax consultants, corporate finance advisors, communications consultants, IT consultants, environmental specialists, and real estate specialists concentrate on particular phases or tasks of the M&A process (Hinne, 2008; Lucks and Meckl, 2015). For example, due diligence tasks are often outsourced to external service providers (Kappler, 2005). The providers assigned in this area are discussed in section 2.2.3.4.

2.1.3 Motives for M&A

Before providing an overview of the degree of attainment of objectives of M&A (see Section 2.1.4), it is essential to understand the motives for entering such transactions (Seth, Song, and Pettit, 2002). Multiple authors such as Lucks and Meckl (2015) or

Seth (1990) split the broad variety of reasons for corporate transactions, from an acquirer's perspective,[22] into two categories: factual-rational, economic motives that build on classical, economic theories (e.g., market-based view) and socio-emotional, personal motives of the acquirer's management that are based on behavioral theories (e.g., hubris theory) (see Figure 2.2) (Lucks and Meckl, 2015).

Figure 2.2: Motives for M&A



Source: Own illustration

Economically justified motives serve to maximize the enterprise value; this connection is in line with the owners' interests. The quintessential example of economic motives is the realization of synergies (Calipha, Tarba, and Brock, 2010). Besides operational synergies, which cover both revenue synergies (e.g., through product diversification, access to complementary customer groups and distribution channels) (Levinson, 1970) and cost synergies (e.g., through economies of scale and scope) (Carpenter and Sanders, 2007; Healy, Palepu, and Ruback, 1992), financial synergies (e.g., through tax benefits, improved credit profiles, facilitated access to capital markets) must also be considered (Carpenter and Sanders, 2007; Ghosh and Jain, 2000). Further economic motives include the development or expansion of market power (e.g., through creation of market entry barriers) (Carpenter and Sanders, 2007; Pennings, Barkema, and Doma, 1994; Trautwein, 1990), a shortened time-to-market compared to organic growth (Hinne, 2008), and access to new capabilities and

[22] For motives from a seller's perspective, refer to Section 2.1.2.2 and to Hinne (2008).

knowledge (Goold and Campbell, 1998). Another objective, which is less strategically and more financially motivated and which is primarily pursued by financial investors, is the identification of undervalued assets and exploitation of arbitrage opportunities (Gonzalez, Vasconcellos, and Kish, 1998).

Personal motives, on the other hand, serve to maximize the utility of the acquiring firm's management and, at best, positively impact the corporate value as a by-product. Investigating a sample of 3,520 transactions in the United States (U.S.), Nguyen, Yung, and Sun (2012) find that 59% of the acquisitions are based on personal management motives. Such motives include undertaking M&A to boost reputation and prestige, gain power, realize salary increases (Lucks and Meckl, 2015; Mueller, 1969; Seth, Song, and Pettit, 2000), diversify risks to secure the executives' positions (Amihud and Lev, 1981), and out of hubris (Roll, 1986).

In reality, there are often overlaps between economic and personal motives, some of which promote and some of which inhibit an increase in company value (Seth et al., 2000). Company value increases also require that the benefits anticipated in the run-up to the transaction are actually realized (Larsson and Finkelstein, 1999). This leads to the question: Is M&A successful? This is examined in the subsequent section.

2.1.4 Success and failure of M&A

The partially conflicting objectives of the stakeholder groups involved (e.g., shareholders, employees, customers, the companies' managements) offer a broad spectrum for investigating the success of such transactions. Consequently, there are different approaches to measuring the success of an acquisition, based on both objective data and subjective assessments of company members or market participants.[23] From this broad spectrum of approaches, the results of success studies from empirical capital market research are presented below.

An overview of the success of M&A transactions is provided by looking at meta-analyses, which collectively evaluate previous study results. Bruner (2002), for example, shows in his meta-analysis of 114 scientific studies that the M&A success for the buyer and target companies combined is slightly positive. In contrast, the meta-

[23] For an overview of different concepts of M&A success measures, refer to Loy and Stammel (2018) and Roediger (2010).

studies by Datta, Pinches, and Narayanan (1992) and King, Dalton, Daily, and Covin (2004) demonstrate that overall success fluctuates around zero – with a tendency towards the negative range. According to these meta-analyses, numerous studies show that the target companies achieve significant positive effects (of up to 20%) as a result of the takeover premium. On the other hand, the acquisition success for the usually much larger investors is slightly negative on average. This finding is underscored by a more recent meta-study by Meckl and Röhrle (2018), who demonstrate that less than half of all transactions are successful from the perspective of the purchasing company.

The large variance of success across the previous studies, paired with the slightly negative effects for acquirers, raises the question: Which factors determine the success or failure of a corporate transaction? Gerpott (1993) provides three approaches for analyzing success and failure determinants: the strategic-structural approach, the integration process-employee-oriented approach, and the corporate culture-oriented approach. Among the determinants of the first explanatory approach are the underlying decision-making and planning processes. Accordingly, the success of a corporate transaction is largely based on the preliminary phase. For instance, Alberts und Varaiya (1989) state that "poor analysis (evaluating incorrectly the implications of plausible projections)" (p. 147) can represent a reason for value destruction. Therefore, the next section is dedicated to the M&A process and afterwards examines the role of FDD as the core of the analyses performed in the M&A process.

2.1.5 M&A process

The mixed results in achieving success through M&A illustrates the need for efficient management of M&A transactions based on a structured procedure. In the previous literature, various M&A process models were developed to systematically represent transaction-related activities. These approaches range from two to seven phases (Calipha et al., 2010). Most models, both in literature and M&A practice, divide the M&A process into three stages (e.g., Jansen, 2000; Lucks and Meckl, 2015; Middelmann, 2000; Picot and Picot, 2012) with substantially congruent but often differently labeled content (Lucks and Meckl, 2015). The essential components of the preparation/planning, transaction/execution, and (post-merger) integration phase are briefly presented below in order to adequately determine FDD's role within the overall M&A process and present it as the focus of this dissertation.

In the preparation phase, the basic strategy is determined on the basis of strategic considerations, especially an analysis of the company and the competitive and acquisition environment (Lucks and Meckl, 2015; Middelmann, 2000). If the basic strategy prescribes a transaction, the subsequent activities depend on the structure of the M&A process (see Figure 2.3). If the seller is initiating the transaction, the seller commences the transaction process (e.g., by creating an information memorandum (IM), conducting a sell-side due diligence) and initiates contact with previously identified potential investors. If the acquirer is initiating the transaction, the investor begins screening potential acquisition candidates, creates a rough valuation and a business case, determines the transaction target, and finally also starts to enter preliminary discussions with the target company (Lucks and Meckl, 2015; Middelmann, 2000). The preparatory phase typically ends with the signing of a letter of intent (LoI) or memorandum of understanding, which underpins that the companies involved have a real interest in the transaction (Lucks and Meckl, 2015).

In the transaction phase, the deal structure (e.g., asset or share deal) is determined. During this phase, the rough valuation of the target and the business case prepared in during the candidate selection process are refined into a detailed valuation and a concrete business plan on the basis of the additional information obtained (e.g., by means of a buy-side due diligence) (Lucks and Meckl, 2015). In parallel, the contracts are negotiated and finally signed (so-called signing) and the legal transition (so-called closing) is prepared. In addition, plans for integration and possible restructuring are developed. Before closing, which marks the beginning of the integration phase, compliance with the transaction must be ensured, in particular by obtaining antitrust and merger control approvals (Lucks and Meckl, 2015).

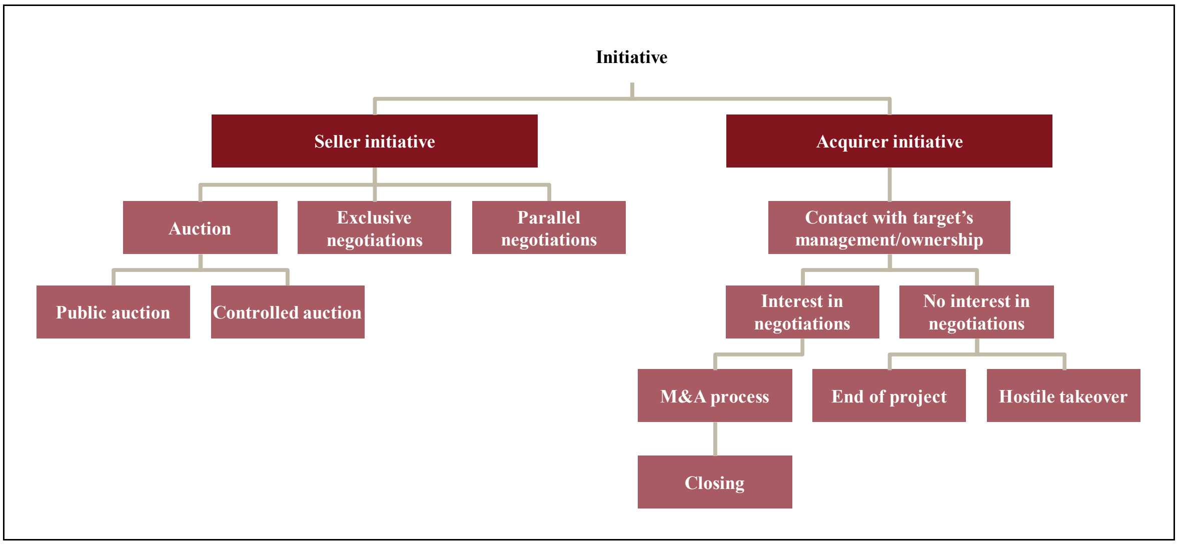
In the final phase, the acquired business will be integrated into existing operations of the strategic buyer (Lucks and Meckl, 2015) or the portfolio firms of financial investors that pursue a buy-and-build strategy. The synergy potential will be realized through adaptations, changes, and restructuring of strategic, organizational, administrative, operational, and cultural determinants (Middelmann, 2000). As a result of these strong post-transactional changes in the acquired company, the corresponding measures are accompanied by an appropriate communication and change management strategy (Lucks and Meckl, 2015). Achievement of the objectives associated with the transaction is continuously monitored (e.g., as part of post-merger audits) and the integration management is adjusted accordingly (Lucks and Meckl, 2015; Middelmann, 2000).

The above descriptions provide an overview of the key building blocks of the three phases. However, it must be considered that some activities can take place across multiple phases. In addition, the M&A process does not represent a purely consecutive sequence of activities, but rather an iterative process with successive information gathering. As a result, some activities are carried out repeatedly (Lucks and Meckl, 2015).

Furthermore, the specific format of the M&A process (in addition to the above-mentioned distinction between the buyer and seller initiatives) depends on the exclusivity of the negotiations. In particular, in cases initiated by the seller, a distinction is drawn between exclusive negotiations, parallel negotiations, and the auction process (Andreas and Beisel, 2017; Lucks and Meckl, 2015; Middelmann, 2000).[24] Exclusive negotiations, in which the seller solely negotiates with an interested party, are most widespread (Andreas and Beisel, 2017; Lucks and Meckl, 2015). This offers a high degree of confidentiality and increases process speed due to comparatively low coordination effort. On the other hand, this approach typically results in a lower purchase price due to lower competition (Lucks and Meckl, 2015). In contrast, during an auction, bids are submitted according to a predefined, formal procedure by preselected bidders (controlled auction) or publicly addressed bidders (public auction) (Andreas and Beisel, 2017; Lucks and Meckl, 2015). Although this format increases the coordination effort, it also regularly leads to a higher purchase price (Lucks and Meckl, 2015). As professionalization of M&A management has increased, a concurrent strong increase in the proportion of controlled auction processes has been observed (Andreas and Beisel, 2017). Parallel negotiations, in which the vendor negotiates with several bidders (Lucks and Meckl, 2015), offer a middle course between these two forms.

[24] For further arguments beyond those outlined in this thesis in favor of the formats presented as well as the implications of the choice of these formats on the design of the M&A process, refer to Lucks and Meckl (2015). The authors also offer a presentation of formats selected after an acquirer's initiative (e.g., hostile takeovers), whose presentation is not of relevance to this dissertation.

Figure 2.3: M&A initiative and processing



Source: Own illustration based on Lucks and Meckl (2015)

2.2 Financial due diligence

The M&A process was presented in the previous subchapter and this subchapter deals with one of its key components: FDD. First, the term *due diligence* is defined (Section 2.2.1), the occasions for carrying it out are described (Section 2.2.2), and it is classified according to the parties involved and the various functional focus areas (Section 2.2.3). The main body of this subchapter presents the objectives of FDD and the process framework. The latter serves as the conceptual basis for identifying use cases of data analytics in the empirical part of this thesis (Section 2.2.4). Additionally, interdependencies between FDD and other M&A process steps are explained (Section 2.2.5). Finally, data analytics technology is critically assessed for the use in FDD in light of the objectives priorly outlined (Section 2.2.6).

2.2.1 Definition of due diligence

The term due diligence originated in the U.S. and is derived from the Security Act of 1933 and the Securities Exchange Act of 1934, both of which were enacted in the aftermath of the 1929 financial crisis (Beisel, 2017a; Grote, 2007; Hollasch, 2013; Pomp, 2015). Both decrees regulate due diligence obligations under capital market law in securities trading (Berens and Strauch, 2013; Reed Lajoux and Elson, 2010). The Securities Exchange Act and Securities and Exchange Commission (SEC) rule 10b-5 of 1942, have been "uncontested since the mid-1960s as the basis for indemnifications in connection with incorrect, misleading, or omitted information provided by the seller in connection with the sale of shares" [translated from German] (Kappler, 2005, p. 23). However, this only results in a basis for liability with regard to incorrect and omitted information that has been provided by the seller in connection with the sale and the contractual agreements (Kappler, 2005). Accordingly, it is the buyer's responsibility to meet its own information needs and negotiate contractual representations and warranties. This form of information gathering used is commonly referred to as due diligence.[25]

There is no overarching definition of the term due diligence (Beisel, 2017a). In contrast, several definitions contain different indications about important discrete features. Kappler (2005) summarizes different definitions and formulates the following comprehensive definition, which is utilized in this thesis:

> Due diligence aims to reduce the prevailing information asymmetry between the transaction parties in the M&A process by analyzing the data provided and by obtaining additional information so that a potential buyer is able to assess all relevant risks and opportunities in the key areas of the target company[26] when making a purchase decision. The findings from due diligence support the buyer in the sales negotiations, the valuation and, in particular, in the subsequent integration of the target company [translated from German] (p. 25).

2.2.2 Occasions for carrying out due diligence

Due diligence is always carried out where two or more parties wish to enter into a contractual relationship with uncertain consequences due to asymmetric information about the present state or future development (Berens and Strauch, 2013).

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[25] Further terms for due diligence include acquisition investigation, acquisition review, business investigation, business review, due diligence process, and due diligence review (Rockholtz, 1999 cited in Kappler, 2005).

[26] The target company can be a group, an individual company (subsidiary), or a business unit. Depending on the transaction object and the available data, due diligence is carried out at either the individual company or the consolidated group level (Pomp, 2015).

In today's commercial parlance, the term is primarily used in the context of corporate transactions (Hölscher, Nestler, and Otto, 2007; Pomp, 2015).[27] However, other events can also trigger a due diligence. They include: (re-)financing, capital market transactions (e.g., an IPO), compensation claims from former shareholders, or venture capital investments in growth companies (Beisel, 2017b; Pomp, 2015; Störk and Hummitzsch, 2017). The following explanations relate solely to due diligence in the course of M&A.

2.2.3 Classification of due diligence

Typically, due diligence can be classified along three categories: functional forms, addressees and initiators, and timing. The three categories are presented below. The section also deals with the M&A service providers that commonly carry out the different forms of due diligence.

2.2.3.1 Functional forms

A distinction is made between different functional focus areas of due diligence (Beisel, 2017a; Blöcher, 2002; Pomp, 2015). The core components that are conducted in almost every transaction are financial, tax, and legal due diligence. In their empirical analysis for the German market, Marten and Köhler (1999) find that financial, tax, and legal due diligence are conducted in 94%, 82%, and 78%, of the investigated M&A transactions, respectively. A corresponding investigation by Berens and Strauch (2011) supports this finding, revealing that financial (including tax) and legal due diligence are carried out in 94.7% and 89.8% of the transactions, respectively. These results underline the preeminent role of FDD. Depending on the target company and the potential buyer, commercial, operational, human resources (HR), IT, compliance/integrity, real estate, and environmental due diligence are also carried out. In some cases, intellectual property, pension, cultural, and technology due diligence are listed as separate forms of due diligence; however, these overlap with the due diligence forms already listed (Pomp, 2015). The execution of the different types of due diligence depends on various factors. The type of buyer, for example, plays an important role in the type of due diligence carried out. CDD is carried out more frequently by financial investors, as they often have less detailed market knowledge than

[27] A special type of corporate transaction is carve-outs, i.e., the acquisitions of newly formed companies through restructuring activities (e.g., spin-offs). Consequently, due diligence in carve-out deals must examine a moving target that previously did not exist on a stand-alone basis (Andreas and Beisel, 2017).

strategic investors. By contrast, compliance/integrity due diligence is mainly carried out by strategic investors (in particular by international groups) to fulfill legal and internal requirements (Pomp, 2015).

Table 2.1 presents an overview of the most common functional forms including the focus of their analysis as well as their relation to FDD. The breadth of functional forms and their interconnection with FDD underscores the central role of FDD. It is under FDD where results from close to all other forms converge.

Table 2.1: Functional forms of due diligence

Functional form	Main focus and interdependencies to financial due diligence
Financial	*Focus:* Analysis of the historical, current, and planned profitability (incl. sustainable earnings), assets and liabilities (incl. net debt), and liquidity/free cash flow (FCF) (incl. working capital and investments)
Tax	*Focus:* Analysis of tax risks (e.g., from reorganizations under company law); determination of tax effects on subsequent years; analysis of possible tax payments from appeal and fiscal court proceedings
	Interdependencies: Quantification of net debt (assessment of income tax liabilities/provisions/risks)
Legal	*Focus:* Identification und quantification of juridical risks (with respect to company law structure, major contracts, labor law contracts, legal disputes, permits and approvals, industrial property rights, change of control clauses)
	Interdependencies: Quantification of net debt (legal risks not yet considered in the balance sheet, such as legal disputes or material guarantee claims); consideration of legal risks in the business plan
Commercial	*Focus:* Analysis of market attractiveness, customer situation, and competitive environment; evaluation of the business model and strategy; validation of the revenues according to the business plan
	Interdependencies: Development of revenues and the gross margin; analyses of FDD (e.g., ABC customer analysis, sales by distribution channels, churn rate analysis, and hit rate analysis) often build the basis for further investigations
Operational	*Focus:* Analysis of operational performance and value drivers; validation of cost planning and investment planning; evaluation of planned restructuring and improvement measures, assessment of synergy effects and carve-out effects
	Interdependencies: Profitability planning (operational cost positions); FCF planning (investments)
HR	*Focus:* Analysis of management competences; analysis of the management incentive system; current personnel structure and its historical and planned development; analysis and valuation of pension and partial retirement obligations
	Interdependencies: Quantification of net debt (pension and partial retirement obligations); plausibility check of the personnel costs
IT	*Focus:* Review of strategic alignment and integration capability of the IT landscape; assessment of infrastructure, business systems, hardware, software, and IT processes; evaluation of the harmonization of the IT landscape between target and buyer (if strategic investor)
	Interdependencies: Quantification of net debt (one-time integration costs, one-time acquisition costs for hardware and software, migration or integration costs); plausibility check of IT costs and investments in the business plan
Compliance/integrity	*Focus:* Audit of compliance with laws, regulatory guidelines, and internal codes of conduct (e.g., compliance management system, compliance guidelines, historical compliance violations)
	Interdependencies: No direct relationship
Real estate	*Focus:* Analysis of footprint, buildings, and property
	Interdependencies: FCF planning (investments)
Environmental	*Focus:* Identification and quantification of environmental risks (e.g., soil and groundwater pollution, fulfilment of binding emission targets)
	Interdependencies: Quantification of net debt (provisions/liabilities related to environmental risks; environmental risks not yet captured in the balance sheet)

Source: Own illustration based on the descriptions in Pomp (2015)

2.2.3.2 Initiator and addressee

A due diligence can be initiated by the seller (sell-side or vendor due diligence (VDD)/assistance) or by the potential buyer (buy-side due diligence) (Blöcher, 2002; Pomp, 2015).[28]

Sell-side assistance/due diligence

On the sell-side, a distinction is made between vendor assistance and VDD (Nawe and Nagel, 2011; Pomp, 2015).[29, 30] Both forms, VDD and vendor assistance, speed up the M&A process, increase the data quality and consistency, and enable the seller to identify problem areas at an early stage (Pomp, 2015; Rosengarten, 2017). A vendor assistance commonly results in a financial data book or financial fact book (Pomp, 2015). The financial data book contains detailed, yet uncommented analyses of the historical and planned earnings situation, asset situation, and financial situation (Nawe and Nagel, 2011; Pomp, 2015). In contrast, the financial fact book contains factual comments; however, the appropriateness of the facts presented is not assessed in the report (Nawe and Nagel, 2011; Pomp, 2015). After preparation, the documents are made available to potential buyers and potential lenders during the M&A sale process on a non-reliance basis (Pomp, 2015). This means that the responsible service provider (see Section 2.2.3.4) enters into a liability relationship only with the client (target), but not with the potential buyers or lenders (Nawe and Nagel, 2011; Pomp, 2015).

As part of VDD, a formal VDD report is prepared. In contrast to the financial data book/fact book, the VDD report contains a critical evaluation that assesses the appropriateness of the facts presented (Pomp, 2015). Moreover, the final VDD report is made available on a reliance basis. This means that the responsible service provider

[28] A third option is the initiation of a due diligence by lenders (Bredy and Strack, 2011; Pomp, 2015); this, however, is beyond the scope of this thesis. Although lenders must be involved in the external financing of the transaction by the strategic investor or the financial investor, they only act as the main addressee in the case of (re-)financing (Pomp, 2015), which is not considered in the context of this dissertation.

[29] A combination of the two types is possible, in which a vendor assistance is followed by VDD such as a “VDD [r]eadiness [a]ssessment” (Pomp, 2015, p. 21).

[30] In addition to VDD, Andreas and Beisel (2017) describe the reverse due diligence as a form of the sell-side due diligence in which the target company carries out a due diligence for internal preparation only. The following references of the term sell-side due diligence, however, refer exclusively to VDD, i.e., a due diligence conducted by the selling party whose information is passed on to potential acquirers.

enters into a liability relationship not only with the client, but also with the final buyer and lender (Nawe and Nagel, 2011; Pomp, 2015).[31] In this instance, the service provider acts as an "independent third party" [translated from German] (Pomp, 2015, p. 22). A VDD report is usually prepared in auction processes (Andreas and Beisel, 2017), for larger transactions, or for deals focused on financial investors as potential buyers (Pomp, 2015). In these cases, the liability risks and buyer claims make it particularly worthwhile to accept the outlay of increased time intensity, costs, and use of management resources.

Buy-side due diligence

Buy-side due diligence may start in advance of the execution phase as soon as financial data is provided in the IM. The core phase for buy-side due diligence, however, is the execution phase of the M&A process (Pomp, 2015). After obtaining access to essential information in the data room, the buy-side due diligence analyses must identify key strengths, weaknesses, opportunities, risks, and value drivers (Nieland, 2002; Pomp, 2015). As with VDD, findings from buy-side due diligence are compiled in a formal report. Also similar to VDD, the buy-side due diligence report is transmitted to potential lenders on a non-reliance basis and, at a later stage, to final lenders on a reliance basis (Pomp, 2015).

The report's results form the basis for determining the enterprise and equity values as well as the purchase price. Buy-side due diligence is essential enabling the potential buyer to submit a binding offer. The results are also taken into account when drafting the purchase agreement as well as an integration plan (Pomp, 2015).

Subsequent analyses take place during the negotiations of the purchase agreement. In this confirmatory due diligence, open points from the previous phase are analyzed, the report is updated to reflect current business developments, and additional analyses are carried out as part of contract negotiations (Pomp, 2015).

Commonly, buy-side due diligence is divided into two phases. The first phase focuses on the identification of deal breakers, which can lead to a termination of the transaction. This phase usually leads to a red flag report that addresses the main risks.[32] Once

[31] For an explanation of the scope of liability, refer to Störk and Hummitzsch (2017).
[32] According to Andreas (2017c), non-remediable transaction-critical deal breakers are rare.

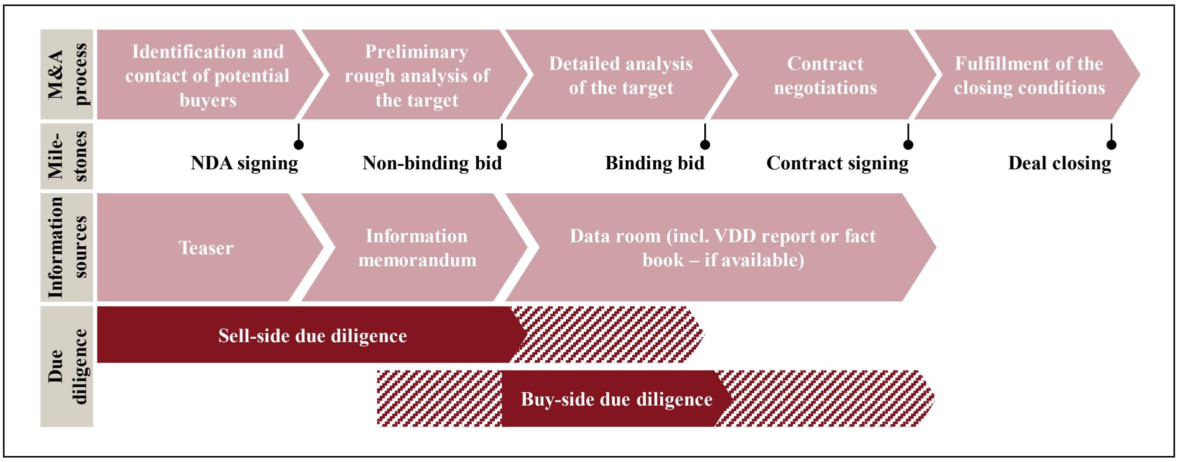
the prospective buyer decides to continue pursuing the transaction (e.g., with purchase price reductions or grant of significant indemnities), the second phase begins. Detailed analyses are carried out, which lead to the above-mentioned comprehensive due diligence report. The buyer benefits from the early recognition of deal breakers (i.e., costs and resources are minimized in the case of an early termination) in this two-phase approach (Pomp, 2015).

2.2.3.3 Timing

Pre-acquisition and post-acquisition due diligence can be differentiated in terms of timing (Blöcher, 2002).

Commonly, due diligence is carried out pre-acquisition, i.e., prior to the signing of the purchase agreement. Rare instances occur where the only due diligence conducted is done post-acquisition. Such circumstances can arise due to a lack of time or due to special confidentiality matters. In such cases, the acquirer has three primary intentions. First, similar to pre-acquisition due diligence, the investor strives to form a comprehensive picture of the target. Second, the investor seeks to secure the purchase price paid and to verify the company's contractually assured characteristics by means of a target-actual comparison. Thus, post-acquisition due diligence serves ex post facto to determine a possible purchase price reduction and/or compensation claims of the buyer against the seller. Third, post-acquisition due diligence is part of the company's risk policy and serves to avoid liability risks (Blöcher, 2002). Due to the practical dominance of pre-acquisition due diligence, the following remarks refer exclusively to this form. Its integration into the timeline of the M&A process (for example in a structured auction) is illustrated in Figure 2.4.

Figure 2.4: Timing of M&A process and due diligence process



Source: Own illustration based on Pomp (2015)

2.2.3.4 External service providers

The different due diligence forms are initiated by either the target, the potential buyers, or their M&A advisors (see Section 2.1.2.2). In practice, sellers and buyers rarely use internal teams to carry out due diligence and involve external parties, except during low complexity transactions (Kappler, 2005). The initiators direct their requests to specific service providers, as each functional form of due diligence requires a different expertise (Pomp, 2015). Table 2.2 shows the typical service providers for the most common forms of due diligence. Some companies, especially the large audit firms, have expertise in multiple disciplines. This positions them to be able to bundle analyses from different areas if optional due diligences (e.g., commercial, operational, HR) are requested to be integrated in the very common due diligence forms (e.g., integration of the commercial part into FDD).

Table 2.2: Due diligence service providers

Functional form	Typical due diligence service providers
Financial	Audit firms
Tax	Tax advisors
Legal	Law firms
Commercial	Strategy consulting firms Special departments of audit firms Smaller consulting firms with specialist knowledge of niche markets
Operational	Consulting firms with operational production expertise

Source: Own illustration based on the descriptions in Pomp (2015)

Grote (2007) writes that in Germany, FDD is only conducted by auditors.[33] Table 2.3 provides an overview of the largest German audit firms in 2018. The Big Four possessed a market share of 86% in non-audit services, which includes due diligence offerings. Moreover, Table 2.4, which has been developed specifically for the purpose of this thesis based on data from S&P Capital IQ, shows that the Big Four firms conducted 7 out 10 FDDs in global M&A deals in the period 01/2000-06/2017 compared to the top 30 service providers. Since the Big Four tend to carry out larger deals, this number is potentially higher in terms of revenue or deal size.

Due to the discrepancy in market share among the firms, it is necessary to make a distinction between the Big Four on the one hand and the medium-sized and small audit firms one the other within this dissertation. Due to their dominant position (and thereby representativeness for a large part of the market), as well as their greater openness towards adoption and use of emerging technologies (Janvrin et al., 2008; Lowe et al., 2017; Rosli et al., 2013), the empirical portion of this thesis primarily focuses on the Big Four. Aspects of particular relevance to medium-sized and smaller audit firms are highlighted separately. Moreover, the quantitative analysis of the questionnaire data in Chapter 6 highlights the statistically significant differences between the Big Four and Next Ten audit firms.

[33] Grote (2007) further explains that “pursuant to §2 I WPO, it is the auditor’s task to carry out business audits, in particular of annual financial statements. Financial due diligence is a business audit that is not a conditional audit and can therefore also be performed by other experts” [translated from German] (Grote, 2007, pp. 103–104).

Table 2.3: FDD service providers – Overview of German audit firms

Rank	Company	Revenues in 2018 (in 1,000 EUR)		
		Total	Audit services	Non-audit services
1	PricewaterhouseCoopers GmbH WPG	1,977,100	423,700	1,553,400
2	Ernst & Young GmbH WPG	1,880,300	302,200	1,578,100
3	KPMG AG WPG	1,710,000	478,000	1,232,000
4	Deloitte GmbH WPG	963,000	131,000	832,000
5	BDO AG WPG	195,342	37,169	158,173
6	Genossenschaftsverband – Verband der Regionen e.V.	146,419	63,779	82,640
7	Mazars GmbH & Co. KG WPG StGB	130,941	34,070	96,871
8	Rödl & Partner GmbH WPG StGB	106,199	36,491	69,708
9	Warth & Klein Grant Thornton AG WPG	91,718	22,282	69,436
10	Ebner Stolz GmbH & Co. KG WPG StGB	79,543	39,285	40,258
11-30	*various*	541,300	208,095	333,206[1]
Total		**7,821,862**	**1,776,071**	**6,045,792[1]**
Share of Big 4		83%	75%	86%[2]
Share of ranks 5-10		10%	13%	9%[2]
Share of ranks 11-30		7%	12%	6%[2]

Notes:

1) Köhler and Ratzinger-Sakel (2019) note that the sum of revenues from audit services and non-audit services differs from total revenues by one unit (i.e., 1,000 EUR).

2) The aggregated market shares of non-audit services amount to 101% as the percentage figures are rounded.

Source: Own illustration based on Köhler and Ratzinger-Sakel (2019)

Table 2.4: FDD service providers – Overview of global audit firms

Rank	Global network brand	Number (share) of financial due diligences between 01/2000 and 06/2017		
		Total FDDs	Thereof sell-side	Thereof buy-side
1	Ernst & Young (EY)[1]	4,940	1,481 (30%)	3,453 (70%)
2	PricewaterhouseCoopers (PwC)[1]	3,731	1,362 (37%)	2,363 (63%)
3	KPMG[1]	3,232	1,196 (37%)	2,030 (63%)
4	Deloitte[1]	2,878	1,016 (35%)	1,856 (64%)
5	Grant Thornton	1,574	442 (28%)	1,132 (72%)
6	BDO[1]	1,536	482 (31%)	1,050 (68%)
7	Mazars	521	116 (22%)	405 (78%)
8	Crowe Global[1]	403	120 (30%)	282 (70%)
9	RSM	362	137 (38%)	225 (62%)
10	Baker Tilly	309	108 (35%)	201 (65%)
11-30	*various*[1]	1,629	383 (24%)	1,244 (76%)
Total[1, 2]		**21,115**	**6,843 (32%)**	**14,241 (67%)**
Share of Big 4		70%	74%	68%
Share of ranks 5-10		22%	21%	23%
Share of ranks 11-30		8%	6%	9%

Notes:
The data is from S&P Capital IQ, which was accessed via the Wharton Research Data Services platform.
1) The difference between the total number of FDDs and the sell-side/buy-side split results from a small number of mandates that could not be allocated to either side. This also explains the possible deviations in the percentage figures from 100%.
2) In addition to the 30 service providers with the highest number of FDDs, there were 2,213 companies that carried out between 1 and 29 FDDs in the 01/2000-06/2017 period (average: 2.37). Due to their small size, these companies are beyond the scope of this analysis.

Source: Own illustration

2.2.4 Financial due diligence process

Following the general definition and classification of due diligence, the subsequent sections deal with FDD in particular. First, the objectives of conducting diligent investigations are outlined. Afterwards, a process framework for FDD is presented and its components are described in detail.

2.2.4.1 Objectives

To understand the specifics of FDD, which need to be considered as part of the process framework (see Section 2.2.4.2), the objectives are briefly outlined. Moreover, the objectives enable a substantial evaluation of the potential process improvements through the inclusion of additional data sources and the use of data analytics (see Sections 2.2.6 and 5.2.8).

Large parts of the literature on FDD do not systematically and comprehensively present the objectives (e.g., through merely implicit mentions or a restriction to the buy-side).[34] After analyzing the literature, the following three overarching objectives have been compiled:

Identification and consideration of risks as well as protection from risks

M&A transactions are always characterized by an information asymmetry between the target company and the potential purchasers (Beisel, 2017a; Lucks and Meckl, 2015). In such situations, investors fear that the target's management could opportunistically exploit its information advantage (Götzen, Müller, and Zahn, 2016; Kappler, 2005). Due diligence serves to reduce information asymmetry (Beisel, 2017a; Grote, 2007; Hollasch, 2013; Matzen, 2018; Pomp, 2015; Störk and Hummitzsch, 2017). For example, it significantly improves the level of information (Blöcher, 2002; Schramm, 2003), enhances data quality, and checks the consistency of financial information stemming from different data sources (Pomp, 2015). Weaknesses and risks are uncovered (Blöcher, 2002; Götzen et al., 2016; Hollasch, 2013; Howson, 2017a; Nieland, 2002; Schramm, 2003) and considered in the valuation, purchase agreement, and negotiations (Beisel, 2017a; Blöcher, 2002; Götzen et al., 2016; Pomp, 2015; Schramm, 2003; Störk and Hummitzsch, 2017). Thus, due diligence plays a preventive role by limiting risks from the transaction (Grote, 2007). On top of that, due diligence advisors suggest an adequate risk mitigation strategy (Matzen, 2018; Nieland, 2002). Importantly, the identification and consideration of risks is not limited to buy-side efforts. The due diligence report also protects the seller in terms of liability.

Identification of value potentials

In addition to covering risks associated with the transaction, due diligence serves to identify the target's essential value drivers (Götzen et al., 2016; Pomp, 2015) and its value potential (Blöcher, 2002). This includes both the success potential of the target itself and the synergy effects resulting from the deal (Nieland, 2002). With its value-oriented analyses, due diligence supports the valuation of the target (Beisel, 2017a; Götzen et al., 2016; Grote, 2007; Hollasch, 2013; Matzen, 2018; Pomp, 2015). It also provides important insights for drafting the purchase agreement and conducting ne-

[34] For example, a comprehensive presentation of functions and objectives of due diligence in general, i.e., not tailored to FDD, can be found in Beisel (2017a). He defines four objectives: analysis of opportunities and risks, documentation of the as-is situation, warranty and liability, and purchase price determination.

gotiations (Blöcher, 2002; Hollasch, 2013; Howson, 2017a; Pomp, 2015). If due diligence is closely connected to post-merger integration, the analyses of due diligence also often serve as the basis for integration plans or 100-day plans after transaction completion (Götzen et al., 2016; Nieland, 2002; Pomp, 2015; Schramm, 2003).

Negotiation and decision-making support

Finally, due diligence serves to support the decision-makers in preparing the transaction (Andreas, 2017c; Bredy and Strack, 2011; Lucks and Meckl, 2015; Störk and Hummitzsch, 2017). Underscoring this view, Blöcher (2002) describes due diligence as the "basis for negotiation, argumentation, and decision for the acquisition or sale of shares" [translated from German] (p. 52). Potential risk areas should be identified as early as possible in the sales process (Pomp, 2015) in order to prevent the risk of wrong decisions (Matzen, 2018). Due diligence also contributes to accelerating and optimizing the M&A process (Pomp, 2015). The presentation of comprehensive, consistent financial information from sell-side due diligence eliminates the need for numerous individual enquiries from potential buyers (Pomp, 2015). VDD also prepares the target's management at an early stage to answer the essential questions of interested investors (Pomp, 2015). Put differently, it allows for a fact-based argumentation, and thus, shortens the negotiations. By enabling consistent decision-making, costs can be avoided and management resources can be saved (Grote, 2007; Pomp, 2015). Lastly, the conduct of due diligence enhances the chances of a successful transaction through increased transparency for all parties (Blöcher, 2002).

2.2.4.2 Process framework

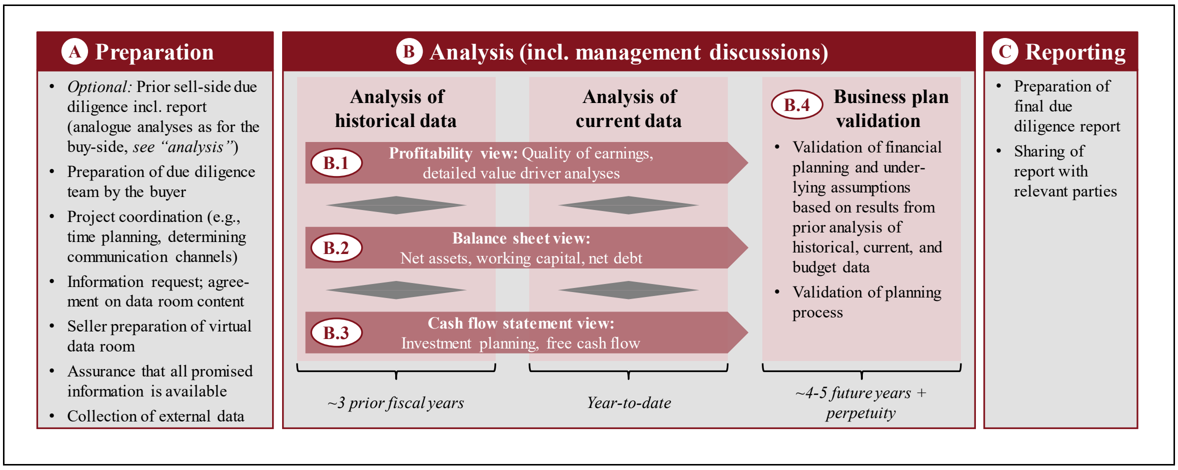
A process framework is applied as the theoretical basis for the investigation of big data and data analytics use cases in FDD. To cover the full spectrum of FDD, this framework considers the report (and not the financial data book or financial fact book) as its final deliverable. However, it must be stressed that "in practice, there is no standard due diligence and each transaction process lives from its specific peculiarities" [translated from German] (Störk and Hummitzsch, 2017, p. 609). For buy-side projects, the lack of norms for FDD, the tight timeframe, and the different objectives of strategic and financial investors require an initial identification of the most important areas from the various fields of investigation. In contrast, in VDD, the target company needs to be examined in sufficient breadth and depth and the scope of work cannot be confined (Störk and Hummitzsch, 2017). Therefore, the following sections are intended to summarize the full scope (i.e., all encompassing) FDD (Hollasch, 2013).

Grote (2007) divides the FDD process into three phases: planning, analysis and monitoring, and reporting. Scott (2002b) posits a similar three-stage process consisting of organization, investigation, and completion. Therefore, the developed process framework is based on three phases: preparation, analysis, and reporting.

Most authors (e.g., Grote, 2007; Lucks and Meckl, 2015) describe the process for buy-side due diligence, i.e., starting after completion of sell-side due diligence. This view be because more buy-side FDDs are carried out than sell-side FDDs (Götzen et al., 2016). As a result, this thesis follows this established process description procedure while also highlighting specifics of sell-side due diligence. In addition, the procedural views on due diligence are enhanced with much more detailed descriptions of the analysis phase from other streams of due diligence literature. Accordingly, the analysis phase of the developed process framework is subdivided.

In the preparation phase, time and resource planning take place and the data room is set up based on previous information requests and analyses (Grote, 2007). The analysis phase focuses on the investigation of historical and current earnings, asset and liability positions, and cash position as well as the business plan validation (Blöcher, 2002; Götzen et al., 2016; Pomp, 2015). For each area, the target's strengths, weaknesses, opportunities, risks, and value drivers are identified (Lucks and Meckl, 2015). Open questions are clarified during the management audit, i.e., discussions with the target's management (Lucks and Meckl, 2015). Finally, findings from the analyses and discussions are summarized in a formal report (Grote, 2007; Lucks and Meckl, 2015). The due diligence process is graphically summarized in Figure 2.5.

Figure 2.5: FDD process framework



Source: Own illustration based on descriptions in Grote (2007) and Pomp (2015)

The concrete design of the due diligence process, in particular the information request and the subsequent analysis phase, depends on several factors. For instance, it depends on the length of due diligence, which ranges from a few days to several weeks depending on the intensity of the investigations and the size of the target (Grote, 2007). Moreover, the review focus and the analyses conducted depend on the target company (e.g., e-commerce vs. project business) (Nieland, 2002; Pomp, 2015), buyer know-how (e.g., strategic buyer with relevant industry know-how vs. financial investor) (Pomp, 2015), and known risk areas (Nieland, 2002). In order to adequately capture these specifics, this work uses a generic process framework and takes particularities into account as they become relevant.

The following sections describe the three phases of FDD (A-C in Figure 2.5) in more detail. Due to the focus on the analysis phase, a separate section is dedicated to each area of analysis (B.1-B.4 in Figure 2.5).

2.2.4.3 Due diligence preparation

The preparation phase does not vary considerably between FDD and other forms of due diligence. Grote (2007) divides this phase into the following activities: time planning, resource planning, determination of communication channels, information request, and confidentiality agreements.

First, the collaboration between the initiator and its advisors are contractually agreed on and the scope and time specifications for the individual tasks must be scheduled.

It is important that the interaction between different teams, such as other due diligence teams or the valuation team, is coordinated to ensure sufficient communication between the sub-disciplines (Grote, 2007). The resource planning by both the initiator and its advisor involves selecting employees to conduct due diligence based on their qualifications, education, experience, industry and functional know-how, and availability (Grote, 2007; Nieland, 2002; Scott, 2002b). Once the team is set up and the time schedule of due diligence is aligned, the formal communication channels between the different parties involved, the deliverable form (report structure, content, format), and a common understanding of the informal relationships between the team members must be established (Grote, 2007; Nieland, 2002). Next, the due diligence team determines the focus areas for investigation (Andreas, 2017a; Scott, 2002b) and prepares a target-specific checklist for the information request (Andreas, 2017a; Grote, 2007).[35] The information requested traditionally includes a broad range of financial accounting and management accounting data and, if a prior sell-side due diligence has been conducted, the sell-side report (Pomp, 2015). Chapter 5 of this thesis examines the extent to which this step also includes non-traditional information (e.g., big data sources) that goes beyond the traditional sources from the finance and accounting functions (Grote, 2007). The target and its consultants provide the information in a physical or virtual data room (Andreas, 2017a; Blöcher, 2002; Grote, 2007; Lucks and Meckl, 2015).[36] Afterwards, potential buyers ensure that all information promised is indeed available (Lucks and Meckl, 2015) and clarify immediate requests in so-called Q&A sessions (Pomp, 2015). The amount of information usually increases stepwise. The greater the interest of the target and potential buyers becomes, the more information is provided and the more access is granted (Blöcher, 2002; Bredy and Strack, 2011). This holds particularly true for the initially restrictive sharing of sensitive data with interested strategic investors, and, especially with direct competitors (Pomp, 2015). Finally, the LoI (including a confidentiality agreement) is signed by the target and the potential acquirers and then expanded to their service

[35] Examples of checklists can be found in Berens, Brauner, and Strauch (2011), Grote (2007), Howson (2017b), Pomp (2015), Scott (2002a), and Störk and Hummitzsch (2017). For the practical use of checklists, refer to Störk and Hummitzsch (2017).

[36] In practice, virtual data rooms have prevailed for a number of reasons (Andreas, 2017a; Götzen et al., 2016; Lucks and Meckl, 2015; Pomp, 2015). Compared to physical data rooms, they make it possible to individually manage user authorizations, track access to specific data, document the information status of the data room users, have multiple interested parties use the data room in parallel, and keep the data room open for a longer period of time (Lucks and Meckl, 2015). They are also better suited for sharing large volumes of data (Andreas, 2017a).

providers (Blöcher, 2002; Grote, 2007; Scott, 2002b).[37] After the LoI is agreed upon, the target's management presents the historical development of the company and its business activities to the potential acquirers. This meeting kicks off the analysis phase of due diligence (Grote, 2007).

Before the essential analyses of FDD are conducted, a general understanding of the relevant industry and the business activities of the target company must be established. This understanding can be achieved via a commercial preliminary analysis. External information (e.g., analyst reports, public information from the media) and, if available, a detailed IM of the seller are used for this purpose (Andreas, 2017a; Kappler, 2005).

The areas subsequently investigated in this phase are presented in the following four sections. They comprise profitability, balance sheet, and cash flow analyses as well as a validation of the business plan.

2.2.4.4 Profitability analysis

Profitability analysis focuses on the quality of earnings, i.e., adjustments of the historical earnings, in order to determine the sustainable earnings. These are an essential basis for the valuation and thus also essential to deriving the purchase price (Bredy and Strack, 2011; Götzen et al., 2016; Nieland, 2002; Pomp, 2015; Störk and Hummitzsch, 2017). In addition, a general understanding of the business model is developed and value drivers are identified through numerous detailed analyses of the historical development of different income statement positions. These positions include revenues by project/product/region/customer, cost of materials, personnel expenses, and other operating expenses/income (Blöcher, 2002; Götzen et al., 2016; Pomp, 2015). Analyses of exchange rate influences on the development of profitability are also conducted. Finally, the current fiscal year's profitability is adjusted for seasonal effects and assessed in terms of the achievability of budgeted objectives (Blöcher, 2002; Pomp, 2015). The pivotal information source is the profit and loss statement (P&L) of the (consolidated) financial statements – usually from the previous three years (Grote, 2007; Nieland, 2002; Pomp, 2015). Further important information sources are the audit reports, the monthly lists of totals and balances, information

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[37] For an overview of the main contents of the LoI, refer to Scott (2002b).

from internal reporting (e.g., management reporting), a detailed statement of provisions, and the auditor's management letter. In the following, the quality of earnings analysis and additional fundamental analyses, which are based on the P&L items, are briefly presented.[38]

Quality of earnings

Sustainable earnings[39] are determined as a foundation for the subsequent valuation of the target and for deriving the purchase price. Necessary adjustments of historical earnings can be distinguished between normalizations and pro forma adjustments. For normalizations, the result is adjusted for one-off, non-recurring, unusual, non-operating income and expenses.[40] Pro forma adjustments (or like for like adjustments) create a comparable income and cost structure between the historical and planning periods (Bredy and Strack, 2011; Pomp, 2015).[41] Indications of possible normalization and adjustment issues are provided in particular by interviews with the target's management and the auditor's management letter.[42] However, the definitive assessment of a situation is ultimately the responsibility of the due diligence teams as "there is neither a prevailing opinion nor a generally applicable standard for calculating a normalized pro forma adjusted EBIT(DA) result" [translated from German] (Pomp, 2015, p. 54). After necessary adjustments are identified, they are allocated to the P&L items in order to create a normalized, pro forma P&L, which serves as the basis for plausibility checks of the business planning (see Section 2.2.4.7) (Götzen et al., 2016; Pomp, 2015).

[38] The analyses depend in part on the presented income statement structure (cost category method or cost of sale method) (Pomp, 2015). For the practical application across different geographies and company sizes, refer to Coenenberg (2018).

[39] In the course of FDD, earnings are generally measured as either earnings before interest and taxes (EBIT) or – most commonly – as earnings before interest, taxes, depreciation, and amortization (EBITDA) (Bredy and Strack, 2011; Götzen et al., 2016; Pomp, 2015).

[40] Examples of normalizations include restructuring costs, profit or loss from the sale of assets, and the reversal of provisions. For further examples, refer to Bredy and Strack (2011), Pomp (2015), and Störk and Hummitzsch (2017).

[41] Examples of pro forma adjustments include changes in the legal structure, changes of the product portfolio or business units, changes of the cost or revenue structure, changes in the production capacities, synergies, and carve-out effects. For further examples, refer to Pomp (2015).

[42] In particular, in sell-side due diligences and buy-side due diligences with exclusive negotiations, the auditor, if released by the target from his confidentiality obligation and released by the potential acquirer and its advisors from his liability (holdharmless letter), may also be interviewed (Bredy and Strack, 2011; Pomp, 2015).

The normalized and adjusted earnings are not only derived for the historical periods but also for the current reporting period (Pomp, 2015). In the year-to-date (YTD) analysis or current year trading (CYT) analysis, industry-specific seasonal effects and non-monthly transactions are scrutinized (Blöcher, 2002; Pomp, 2015). The year-to-go (YTG) analysis examines the share of annual earnings generated in the remainder of the fiscal year based on previous years' seasonal patterns. The budgeted result's achievability for the entire financial year is assessed on the basis of comparisons of the adjusted YTD and YTG earnings with the previous year's results. These planned earnings are validated with the most recent corresponding data, which can be either the normalized, adjusted YTD and YTG figures or the last twelve months earnings that are not exposed to seasonality. An assessment of the achievability of the budgeted profitability is of utmost relevance to prospective buyers. They often carry out the valuation of the target using the multiplier method on the basis of the budgeted earnings (Pomp, 2015).

Revenues

Typical revenue analyses include the investigation of revenue streams, examination of gross/net revenues, and different breakdowns of revenues. The concrete scope and detail level of the analyses depend, on the one hand, on the target company and the industry it operates in and, on the other hand, on whether a CDD is carried out in addition to an FDD (Pomp, 2015).

Initially, the different types of revenues should be analyzed separately because they are subject to different influencing factors and profitability profiles (Götzen et al., 2016; Pomp, 2015).

Furthermore, gross revenues are reduced by sales deductions such as loyalty rebates, cash discounts for prompt payment, credit notes, and bonuses (Blöcher, 2002; Coenenberg, 2018; Baetge, Kirsch, and Thiele, 2017; Pomp, 2015). If such sales deductions have a significant influence on profitability, a detailed analysis must be carried out (e.g., for e-commerce companies or wholesalers) (Pomp, 2015).

The breakdowns of revenues are typically conducted by (i) business units/divisions/segments, (ii) product groups/locations (stores), (iii) projects, (iv) customers, (v) distribution channels, and (vi) countries (Bredy and Strack, 2011; Pomp, 2015). If the target breaks down its financial data into individual business areas, the first breakdown is executed by (i) business units/divisions/segments. It typically serves as the starting point for further detailed analyses that are also executed by business area. Another core breakdown is conducted by (ii) product groups and locations or stores. This includes the clarification of reconciliation differences between detailed revenue information (commonly from management accounting sources) and total revenues as per P&L (Pomp, 2015). Subsequent to the reconciliation, price-volume effect are analyzed to identify historical revenue drivers (Blöcher, 2002; Nieland, 2002; Pomp, 2015). Depending on the target's industry focus, the historical revenue development is divided into price and volume effects. Additionally, the mix effects due to shifts between products/product groups/locations/branches[43] are determined at the level of the company as a whole. In the case of target companies that are active in the project business, the basis for revenue recognition must be examined. The (iii) project revenues recorded under to the completed contract method are reconciled using the internationally applied percentage-of-completion method to normalize the potentially distorted historical earnings trend. In addition, the historical success rate of tenders and bids is examined (hit rate analysis) (Pomp, 2015). Another core breakdown examines revenues by (iv) customers. It includes an ABC customer analysis to identify potential dependencies on key accounts and a churn rate (or attrition rate) analysis (Blöcher, 2002; Pomp, 2015; Störk and Hummitzsch, 2017). Another breakdown may be executed by (v) distribution channels. Corresponding investigations include the shares of revenue via direct (e.g., stores, personal direct sales, telephone sales, e-commerce) and indirect sales (e.g., commercial agents, wholesalers, retailers, franchisees) as well as, comparable to the breakdown by locations, a price-volume analysis. For strategic investors, the fit with the target's distribution channels may be analyzed. Finally, the geographical revenue split by (vi) countries can be performed using either the revenues of local subsidiaries or local clients (Blöcher, 2002; Pomp, 2015).

Profitability

Analogously to revenues, profitability[44] is analyzed with the help of different breakdowns. The analyses are usually carried out according to product groups, locations,

[43] Pomp (2015) remarks that these analyses strongly depend on the availability of data. The shift towards increasing data availability and resulting opportunities for the profitability analysis are discussed in Sections 5.2.1 and 5.2.3, respectively.

[44] In the course of FDD, profitability is commonly measured as gross profit and gross margin, respectively (Pomp, 2015; Störk and Hummitzsch, 2017).

or are project-specific. Depending on data availability, additional analyses are performed by customer or by distribution channel (Pomp, 2015). Typical examinations on the product group/location level include, similarly to the revenue analysis, clarifications of reconciliation differences between gross profit, on a less aggregated level, and total gross profit. Examinations also include a price-volume analysis. In addition, a pro forma reconciliation between the completed contracts method to the percentage-of-completion method is carried out at the project level. At this point, individual, significant projects are assessed in detail with regard to their margins, time planning, possible risks, and impeding loss provisions (Pomp, 2015).

Cost of materials

The cost of materials (in accordance with the cost category method) includes the cost of raw materials and supplies as well as purchased goods and services (Pomp, 2015). In the case of material-intensive targets, the cost of materials and the development of the material cost ratio are examined in detail (Blöcher, 2002; Pomp, 2015). Depending on data availability, cost of materials is disaggregated by product groups/locations/divisions/countries (Pomp, 2015). Material costs are broken down by main supplier to analyze the target's dependence on individual suppliers (Blöcher, 2002; Nieland, 2002; Pomp, 2015; Störk and Hummitzsch, 2017). Depending on the type of investor, the potential synergies such as improved purchasing conditions, volume discounts through increasing order quantities, and use of cheap substitutes are assessed (Nieland, 2002; Pomp, 2015).

Personnel costs

The personnel costs (in accordance with the cost category method) include wages and salaries, social security contributions, and expenses for pensions and other benefits (Pomp, 2015). In the case of personnel-intensive target companies, detailed analyses of the personnel costs and their components, the development of the personnel cost ratio, and the personnel costs per employee are carried out and compared to competitors. Moreover, the historical development of the number of employees (using FTE instead of heads) and the current personnel structure (e.g., by functions) are examined. In some cases, analyses are conducted of the fluctuation rates, sickness rates, labor union density, willingness to strike, length of service, age structure, or capabilities and qualifications (Bredy and Strack, 2011; Nieland, 2002; Pomp, 2015; Störk and Hummitzsch, 2017).

Other operating expenses/income

The composition and historical development of other operating expenses/income are assessed and the corresponding analyses serve as the basis for identifying normalization circumstances. Normalization plays a crucial role, since other operating expenses/income are characterized in particular by one-off, non-recurring effects (e.g., expense: bad debt loss; income: receipt of payments on impaired receivables) (Bredy and Strack, 2011; Pomp, 2015; Störk and Hummitzsch, 2017).

Foreign exchange rate

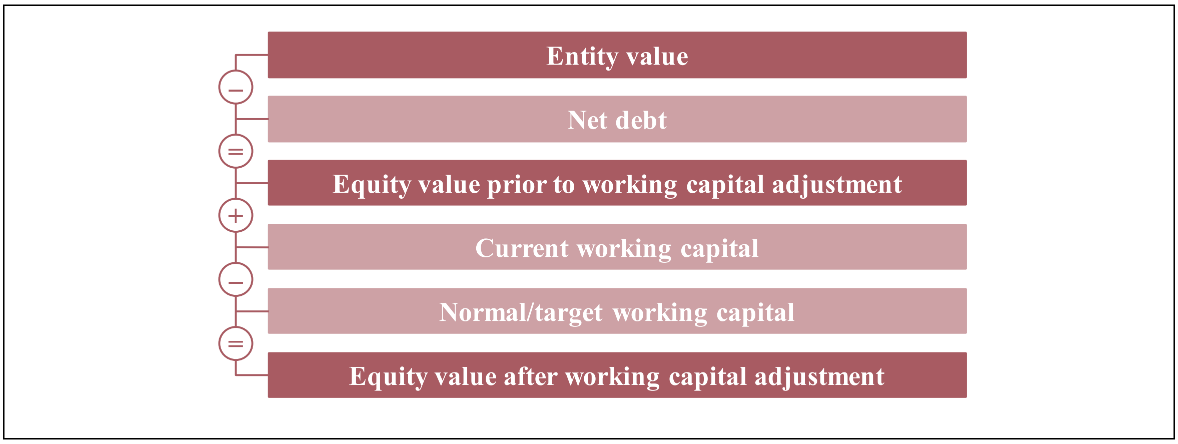
The development of earnings may be influenced by changes in exchange rates, in particular for groups with subsidiaries abroad and regularly occurring international transactions (i.e., purchase/sale of goods/services in foreign currencies). For this reason, the impact of changes in currency exchange rates is quantified by calculating translation and transaction effects. The translation effect examines "how the change in exchange rates affected the currency translation of the P&L from the local currency [of the foreign subsidiary] to the group currency" [translated from German] (Pomp, 2015, p. 114). The constant currency analysis quantifies the translation effect and measures how earnings would have developed if exchange rates had remained constant over the period under review. By contrast, the transaction effect analyzes "the influence of exchange rate fluctuations on the sale or purchase of products/services in foreign currencies" [translated from German] (Pomp, 2015, p. 117). The transaction effect is determined by recalculating all transactions at constant rather than historical rates. The constant exchange rates correspond to the business plan's rates to allow for comparison between historical and future periods (Pomp, 2015).

2.2.4.5 Balance sheet analysis

The balance sheet analysis focuses on the review and reclassification of (i) net debt, (ii) working capital, and (iii) fixed assets (Götzen et al., 2016; Pomp, 2015). This involves the identification of both valuation reserves (to release funds or refinance a transaction) and payment requirements (resulting in a cash outflow or financing requirement after the transaction) (Götzen et al., 2016). The fourth component, (iv) equity, does not require detailed analysis as it represents a residual value.

The balance sheet analysis begins with the identification and quantification of (i) net debt items. Net debt is the difference between financial liabilities and financial assets as well as excess cash (i.e., non-operating cash and cash equivalents). Identifying the net debt position is essential for deriving the purchase price, because the valuation is generally based on the assumption that the target is "cash and debt free" (Pomp, 2015, p. 173; see also Bredy and Strack, 2011). More detailed analyses of the net debt positions may reveal balance sheet risks (e.g., resulting from overvalued assets, undervalued liabilities, and/or unrecognized liabilities), leading to an increase of net debt or a decrease of working capital (Nieland, 2002; Pomp, 2015). The interaction between net debt and earnings adjustments must also be taken into account. Another essential component of the balance sheet analysis is the identification and quantification of (ii) working capital, which may also lead to purchase price adjustments. Detailed working capital analyses are performed on inventories, accounts receivable, and accounts payable (Pomp, 2015). Figure 2.6 shows the impact of net debt and working capital on the target's equity value. The target's equity value is derived from the entity value by subtracting net debt and adjusting for the difference between current and normal level of working capital (Baetge, Niemeyer, Kümmel, and Schulz, 2014). Items already included in the calculation of enterprise value are not deducted again as part of net debt (Götzen et al., 2016).

Figure 2.6: Determination of the equity value



Source: Own illustration based on Pomp (2015)

The third component of the balance sheet analysis is (iii) fixed assets, which are i.a. tested for a potential capital expenditures (Capex) backlog (Pomp, 2015). Of note, international transactions may require adjusting the accounting standards used (Blöcher, 2002). Accounting methods may also be adjusted to those standards and methods applied by potential investors. This procedure facilitates the comparison between the financial statements of the target and the investor (Nieland, 2002).

The most important input sources for the analyses of fixed assets are historical balance sheets from the three prior fiscal year-ends and from the current figures, lists of totals and balances, the statement of changes in fixed assets, and the statement of changes in provisions. However, the balance sheet is formatted differently in FDD than in commercial law. There are three typical format options for presenting the balance sheet as part of FDD: sources and use, capital employed, and net assets. The commonality of these formats is that the net debt and working capital definitions are net positions, i.e., the items included in each position are netted assets and liabilities. For example, in contrast to the allocation applied in the reported balance sheet, liabilities and provisions classified as working capital are allocated to uses and not sources. Further differing from the balance sheet format, all three format options explicitly present the information relevant to the purchase price, such as net debt, to an FDD initiator (Pomp, 2015). In the following, the three areas of analyses (net debt, working capital, fixed assets) and the residual amount (equity) are presented briefly.

Net debt

The quantification of net debt is a core analysis in FDD. In practice, net debt usually includes financial liabilities, financial assets, and excess cash. If the non-operating cash and cash equivalents, as well as the financial assets, exceed the financial liabilities, net assets are reported instead of net debt. In contrast to working capital, net debt also includes non-operating balance sheet items. The distinction between working capital and net financial liabilities is largely subjective and there is no prevailing opinion or standard. The differing interests of sellers and potential buyers often strongly influence the assessment as to whether individual positions should be included in the calculation of net financial liabilities. Crucially, once an item is quantified as net debt, interdependencies with adjusted earnings must be considered. If these interdependencies are not taken into account, items that are accounted for as net debt would also reduce earnings and thus lead to a double deduction from the enterprise value (Pomp, 2015). When identifying and quantifying net debt, a distinction is made between on and off-balance sheet net debt (Götzen et al., 2016; Pomp, 2015). Relevant on-balance sheet items include the net debt in a narrower sense (financial liabilities, financial assets, excess cash) as well as debt-like items (e.g., restructuring provisions). Off-balance sheet items include undervalued/overvalued assets and liabilities as well as items not listed on the balance sheet at all (Pomp, 2015).

Working capital

FDD deviates from the conventional definition of working capital or current assets, which typically include inventories, accounts receivable, other assets, securities, and cash and cash equivalents. In the context of due diligence, working capital includes "all balance sheet items that are directly related to the production process or ordinary business operations, unless they are allocated to fixed assets or bear interest" [translated from German] (Pomp, 2015, p. 175). The position is divided into working capital in the narrower sense (inventories, accounts receivable, accounts payable) and in the broader sense (additionally: other current assets,[45] other current liabilities, other provisions, accruals) (Götzen et al., 2016; Pomp, 2015). Due diligence needs to allocate the different positions of other current assets, other current liabilities, and other provisions to either working capital or net debt (Pomp, 2015). For working capital in the narrower sense, (i) inventories, (ii) accounts receivable, and (iii) accounts payable are analyzed (Pomp, 2015) for their value retention, seasonality, sustainability, and are also analyzed for changes/trends in the course of the business (Götzen et al., 2016). The analyses of (i) inventories typically focus on raw materials and supplies, work in progress (WIP), finished goods, and advances to suppliers. For raw materials and supplies, the influences of simplified valuation procedures (e.g., last-in, first-out (LIFO), first-in, first-out (FIFO))[46] and price changes are taken into account (e.g., creation of hidden reserves in LIFO procedures and price increases) (Pomp, 2015). Potential over or undervaluation is identified (Nieland, 2002). Further analyses of the raw materials and supplies include the historical development of write-downs, an age structure analysis, a turnover frequency analysis, and a coverage analysis (Bredy and Strack, 2011; Grote, 2007; Nieland, 2002; Pomp, 2015; Störk and Hummitzsch, 2017). The latter provides information on whether clusters or individual items have a very long coverage range and on whether write-downs have been or should be created accordingly (Pomp, 2015). The use of inclusion options in inventoriable costs is examined in the context of WIP. In addition, particularly in the project-based services, application of the completed contract method and the percentage-of-completion method must be taken into account and the project valuation must be reviewed critically (Grote, 2007; Pomp, 2015; Störk and Hummitzsch, 2017). As with raw materi-

[45] Other current assets allocated to working capital in the broader sense also include cash and cash equivalents required for operations (Pomp, 2015).

[46] While IFRS prohibit the use of LIFO accounting (IAS 2), US-GAAP (like further local GAAP) allow companies to decide between LIFO and FIFO accounting (ASC 330).

als and supplies, finished goods analyses include a review of the historical development of write-downs, an age structure analysis, and a coverage analysis (Pomp, 2015). The (ii) accounts receivable are classified into either working capital (e.g., receivables related to the operating business) or assets within the net debt position (e.g., receivables not related to the operating business, receivables of a financing nature). Possible distortions due to factoring are taken into account. Moreover, the development of individual and general write-downs is examined to identify normalizations (Pomp, 2015). Breaking down receivables by debtors allows conclusions to be drawn about the main customers. For example, these conclusions relate to payment terms and bonus agreements (Bredy and Strack, 2011; Grote, 2007; Nieland, 2002; Pomp, 2015). An age structure analysis can provide information about the age and maturity of the receivables (Bredy and Strack, 2011; Grote, 2007; Pomp, 2015). The individual items of (iii) accounts payable are initially allocated to working capital or net debt. Subsequently, a breakdown by vendor and further analyses of payment terms and bonus agreements, as well as an age structure analysis, are carried out (Grote, 2007; Nieland, 2002; Pomp, 2015).

Fixed assets

Fixed assets consist of (i) intangible assets, (ii) property, plant, and equipment (PPE), and (iii) financial assets (Götzen et al., 2016; Pomp, 2015). The analysis of fixed assets focuses on the application of accounting principles, a potential Capex backlog, and the allocation of financial assets to net debt. The analysis of both (i) intangible assets and (ii) PPE compares historical investments in these items with the historical cash flows (Pomp, 2015). The exercise of capitalization options is also examined (Nieland, 2002; Pomp, 2015). Finally, the depreciation method is applied and the results are compared to the amount of depreciation in the P&L (Grote, 2007; Pomp, 2015). For (ii) PPE in particular, assets are tested for hidden reserves (i.e., fair value > book value) (Götzen et al., 2016; Grote, 2007; Nieland, 2002; Pomp, 2015; Reed Lajoux and Elson, 2010; Störk and Hummitzsch, 2017). Moreover, non-operational PPE is identified and classified as an asset within the net debt position instead of as a fixed asset (Götzen et al., 2016; Pomp, 2015; Störk and Hummitzsch, 2017). Especially for capital-intensive targets, it is important to compare the degree of wear and tear of technical equipment and machinery with that of competition (Pomp, 2015). This analysis reveals the need for replacement investments (Capex backlog) and helps validate the business plan (Bredy and Strack, 2011; Grote, 2007; Pomp, 2015). Lastly, (iii) financial assets are checked for a reclassification as assets within the net debt position instead of as fixed assets. Consequently, related earnings also need to be reclassified (Pomp, 2015).

Equity

Equity is the residual amount after all other balance sheet items have been classified as either fixed assets, working capital, or net debt (Nieland, 2002; Pomp, 2015). It consists of the share capital (common stock), preferred stock, capital surplus, retained earnings, profit/loss carried forward, profit/loss for the year, treasury stock, stock options, and reserve. The treatment of hybrid equity instruments or mezzanine financial instruments (e.g., profit participation rights) as either net debt or equity is assessed as part of FDD (Pomp, 2015). Apart from that, equity as a residual value does not require a detailed and critical examination because the other balance sheet items have already been examined (Nieland, 2002).

2.2.4.6 Cash flow analysis

The analysis of the historical financial position concentrates on cash and treasury management as well as working capital (Blöcher, 2002). The focus of this analysis is the determination of the FCF, which has a significant influence on the enterprise value under the discounted cash flow (DCF) method (Bredy and Strack, 2011; Grote, 2007; Pomp, 2015; Störk and Hummitzsch, 2017).[47] Although the FCF, in contrast to the historical earnings and asset position, is not influenced by accounting policy measures, it can nevertheless be partially distorted by one-off, non-recurring effects. Thus, the aim is to determine the sustainable FCF by adjusting the historical FCF (Pomp, 2015). Using an indirect approach, the cash flow adjustments take into account the results of the prior profitability and balance sheet analyses (Blöcher, 2002; Nieland, 2002; Pomp, 2015).[48] Determining the sustainable working capital (including target working capital) and the sustainable investments serve as important elements in deriving the sustainable FCF and require supplemental analyses (Pomp, 2015).

[47] For different valuation approaches, refer to Ballwieser and Hachmeister (2016) and Peemöller (2014).

[48] Due to the significantly higher practical relevance (Blöcher, 2002; Pomp, 2015; Störk and Hummitzsch, 2017), e.g. due to limited availability of direct cash flow data (Brauner and Neufang, 2011; Bredy and Strack, 2011), the indirect method for determining the FCF is primarily considered in this thesis.

Free cash flow

The FCF, defined as "the financial surpluses of the target company resulting from normal business operations" [translated from German] (Pomp, 2015, p. 230), can be determined using the direct or indirect method. Using the direct approach, cash receipts are compared to cash expenses in a given period (Pomp, 2015). In practice, the indirect method has prevailed due to the lack of available data or the high expenditure of time necessary for data acquisition required for application of the direct approach (Blöcher, 2002; Götzen et al., 2016; Pomp, 2015; Störk and Hummitzsch, 2017). The FCF is derived from the P&L and from changes in individual balance sheet items and investment activity previously analyzed. Concretely, the EBITDA is adjusted for Capex and divestments, changes in working capital, and, depending on the definition, income taxes (Ballwieser and Hachmeister, 2016; Götzen et al., 2016). Earnings are therefore adjusted for non-cash items (Horváth, 2011).

Working capital

There are two purposes for analyzing the historical development of working capital. On the one hand, it forms the basis for the analysis of the sustainable FCF and, on the other hand, the target working capital must be derived to adjust the purchase price accordingly (Götzen et al., 2016; Gruhn, 2013; Hollasch, 2013; Nieland, 2002; Pomp, 2015). To support the first purpose, working capital is reduced by debt-like items and normalized for one-off, non-recurring effects. The normal level is determined on the basis of the adjusted and normalized working capital. Typically, target working capital is calculated as the average of the previous one to two years. The reference period includes complete annual cycles to take seasonality into account. In order to allow fast-growing companies to maintain an appropriate level of representativeness, the reference period can be restricted to one year and reflect a corresponding growth rate (Pomp, 2015).

In addition to the two main purposes outlined above, working capital is analyzed in more detail to identify potential risks and areas of improvement. For instance, the development of working capital throughout the year is examined using various key metrics such as the cash conversion cycle (CCC). The CCC includes the measures days sales outstanding (DSO), days inventory outstanding (DIO), and days payable outstanding (DPO) (Küting and Weber, 2015; Pomp, 2015).[49] The range of working capital fluctuation must also be analyzed in order to identify effects during the year and adequately consider them when arranging the transaction's financing (Pomp, 2015).

Capital expenditures

First, investments must be normalized and adjusted for Capex related to net debt as well as non-sustainable divestments (e.g., sale-and-lease-back). Next, in a fixed assets roll forward analysis, the development of fixed assets is reconciled between the fiscal year-ends to discover special issues in investments, depreciation, and amortization (Pomp, 2015). Finally, investments can be distinguished between maintenance and expansion investments to provide an outlook in terms of investment needs. While maintenance investments serve to maintain operational efficiency, expansion investments aim to expand operational efficiency (Bredy and Strack, 2011; Pomp, 2015; Störk and Hummitzsch, 2017). However, it is often impossible, or only roughly possible, for the target companies to divide the historical investments into these two categories (Pomp, 2015).

2.2.4.7 Business plan validation

With regard to future business development, the planning calculations and underlying premises and the planning system and process examined (Blöcher, 2002; Grote, 2007; Störk and Hummitzsch, 2017). The planned P&L, the planned balance sheet, and the planned cash flow statement are the main sources for validation of the integrated business plan (Pomp, 2015).[50] However, the level of detail and the definition of planning parameters are usually less granular than historical and current accounting information. Commonly, their structure and their level of detail are comparable to those used in management reporting or internal accounting reporting (Pomp, 2015). In the following section, the main areas of the business plan validation are presented.

Planning process and premises

When validating the planning process, the first step is determining the chosen planning approach (top-down, bottom-up, countercurrent method) (Bredy and Strack, 2011; Pomp, 2015). In practice, use of the countercurrent method is most widespread

[49] The CCC is calculated as the sum of DSO and DIO subtracted by DPO and reflects the working capital turnover time (Küting and Weber, 2015).

[50] For detailed descriptions of integrated financial planning, refer to Hahn and Hungenberg (2001).

as it is a hybrid of the other two possible planning styles (Bredy and Strack, 2011; Horváth, 2011; Pomp, 2015). Next, planning accuracy (e.g., deviations between planned and actual results) is assessed for the previous years (Bredy and Strack, 2011; Störk and Hummitzsch, 2017) and the granularity of the planning is reviewed (Pomp, 2015). Typically, the first year (i.e., the budget) is planned on a monthly basis, whereas the following three to four years are planned on an annual basis. Finally, the granularity of the premises is checked. This can vary greatly since the assumptions mostly relate to the industry and company-specific planning level (e.g., projects, product groups, and price/volume developments) (Pomp, 2015).

Profitability planning

The planned earnings development may have a direct influence on the purchase price if an income-oriented valuation approach (e.g., multiples) is used. According to Götzen et al. (2016), the multiple-based valuation is the most frequently applied method for small and medium-sized enterprises (SMEs). Conversely, the planned earnings development may have an indirect influence, through its significant impact on FCF, if a cash flow-based approach (e.g., DCF) is applied. Core task of an FDD is therefore to validate future planned earnings (Bredy and Strack, 2011; Pomp, 2015).

Initially, the budgeting accuracy is checked by comparing the planning calculations of the previous years with the actual and normalized historical earnings (Blöcher, 2002; Bredy and Strack, 2011; Grote, 2007; Pomp, 2015). Past variances are thus identified, analyzed in more detail, and checked again with regard to the current business plan. If extraordinary items (e.g., restructuring expenses) have already been planned, the next step is to create a normalized planned result (Pomp, 2015). At this phase, the main premises on which profit planning is based are checked (Bredy and Strack, 2011; Götzen et al., 2016; Grote, 2007; Pomp, 2015). The feasibility of these assumptions is subsequently examined on the basis of historical developments, benchmark analyses, external market studies, and expert assessments (Pomp, 2015). In accordance with the analysis of the historical and current earnings situation (see Section 2.2.4.4), analyses may be carried out of planned revenues, profitability, cost of materials, personnel costs, and other operating expenses/income. The scope and degree of detail of these examinations depend on the analyses that have already been carried out on the historical situation, the degree of sophistication of the planning process, and on whether a commercial or operational due diligence is carried out in addition to an FDD (Pomp, 2015). The detailed analyses of the planning premises make it possible to assess the feasibility of the planned development of profitability. They also make it possible to identify strengths, weaknesses, risks, and opportunities in the business plan (Pomp, 2015). Lastly, sensitivity and scenario analyses are used to present the impact of changes to potentially implausible assumptions on earnings (Blöcher, 2002; Bredy and Strack, 2011; Pomp, 2015).[51] The upside potential and downside risks of the business plan are examined individually as an alternative or as a supplement (Pomp, 2015).

Balance sheet and cash flow planning

A feasibility assessment of the planned FCF rests on two pillars: first, the historical analyses of the balance sheet and the cash flow statement and second, the findings of the analyses of planned profitability, working capital, and investments (Hollasch, 2013; Pomp, 2015). Aside from the analysis of various balance sheet positions, working capital and Capex are of the utmost importance. Working capital planning is examined for plausibility using the DSO, DIO, and DPO metrics. These key figures are broken down by regions, subsidiaries, distribution channels, customers, and/or suppliers in order to analyze the drivers of historical and planned changes. The plans can be further validated by benchmarking with performance the main competitors' indicators. When analyzing the investment planning, a comparison is made to the sustainable historical investments. In particular, this requires examining whether a possible Capex backlog necessitates higher maintenance investments and whether the plans must be corrected accordingly. Additionally, the assessment of technical experts or the results of operational due diligence can be used to conduct plausibility checks (Pomp, 2015). In the final validation of the planned FCF, the previous analyses of the projected results and balance sheet items are included. Analogous to the planned profitability analysis, sensitivity and scenario analyses may be performed to determine purchase price ranges (Pomp, 2015).

[51] While sensitivity analyses examine the effect of varying one parameter while other parameters remain constant, scenario analyses change multiple parameters within scenarios (Baum, Coenenberg, and Günther, 2013; Pomp, 2015).

2.2.4.8 Due diligence reporting

The findings from the various analyses and management discussions are summarized in a due diligence report (Grote, 2007).[52] The documentation and subsequent reporting has to serve various functions, such as "communication, monitoring, decision basis, contract preparation, evidence and reconstruction as well as exculpation" [translated from German] (Grote, 2007, p. 116). The due diligence documentation contains working papers, memoranda, and a final report as the auditor's main deliverable in order to fulfill these functions (Andreas, 2017b; Grote, 2007). In addition to a cover letter that includes a brief description of the assignment, the report typically consists of an executive summary or presentation of deal issues,[53] a list of the documents provided by the target company, a description of the investigated areas, and the individual results including their financial impact as well as comments by the auditor (Andreas, 2017b; Grote, 2007; Nieland, 2002; Störk and Hummitzsch, 2017). Of note, the professional organization of auditors provides no standardized guidelines for structuring the FDD report (Andreas, 2017b; Grote, 2007; Störk and Hummitzsch, 2017).

2.2.5 Role of financial due diligence in the M&A process

As outlined in previous sections, FDD has multiple intersections with other activities in the M&A process. The three most important intersections are presented below. As highlighted in Kappler's (2005) definition of FDD utilized in this thesis, they relate to (i) the company valuation for determining the purchase price (Bredy and Strack, 2011; Grote, 2007; Hollasch, 2013; Pomp, 2015; Störk and Hummitzsch, 2017), (ii) the formulation of the purchase agreement (Bredy and Strack, 2011; Pomp, 2015; Störk and Hummitzsch, 2017), and (iii) integration management (Götzen et al., 2016; Grote, 2007; Pomp, 2015).

The (i) determination of the purchase price is based on a previous company valuation, which in practice is usually carried out using a DCF or a multiplier method (Pomp,

[52] For an overview of less comprehensive final documents (e.g., due diligence memorandum, comment letter, opinion letter, mini report), refer to Scott (2002b).

[53] While the more neutral executive summary is contained in VDD reports, the deal issues are presented in buy-side due diligence reports (Störk and Hummitzsch, 2017).

2015). Important parameters of both approaches are derived from FDD, which pertains to the sustainable FCF, the main influencing factor for the DCF approach.[54] In FDD, significant risks, weaknesses, and opportunities in the planned development of the FCF are identified and quantified on the basis of a scenario and/or sensitivity analysis (Pomp, 2015; Störk and Hummitzsch, 2017). In addition, the most commonly used trading and transaction multiples are based on sustainable EBIT(DA), which is also determined in FDD by taking into account normalizations and pro forma adjustments. Finally, the net debt position calculated in FDD is deducted from the entity value and the working capital is adjusted based on the normal level calculated in FDD to derive the equity value (Hollasch, 2013; Pomp, 2015; Störk and Hummitzsch, 2017). In practice, due to the company valuation's significant dependency on FDD, a rough valuation is first carried out, which is refined into a detailed valuation on the basis of the results of FDD and other work streams (Pomp, 2015). FDD differs from company valuation in that it allows for disclosure and makes it possible to assess qualitative factors (Störk and Hummitzsch, 2017). Consequently, value and price-relevant aspects might be renegotiated and reconsidered in the company valuation based on FDD findings (Grote, 2007; Hollasch, 2013; Störk and Hummitzsch, 2017).

FDD also evinces a strong connection to (ii) the negotiation of the purchase agreement (Pomp, 2015; Störk and Hummitzsch, 2017). For example, findings from FDD that do not result in a direct purchase price reduction (e.g., due to a lack of quantifiability) are taken into account via representations and warranty clauses in the purchase agreement (Bredy and Strack, 2011; Pomp, 2015; Störk and Hummitzsch, 2017). The reliability of the historical results determined in FDD can contribute to the decision regarding the purchase price mechanism (completion accounts vs. locked box) (Pomp, 2015). Finally, the specification of normalizations in the calculation of sustainable earnings may be embedded in the purchase agreement as a reference for earn-out clauses (Pomp, 2015).

The third important FDD intersection is with (iii) (post-merger) integration. The results of FDD serve as the basis for integration planning (Grote, 2007; Pomp, 2015);

[54] The FCF used in company valuation and FDD differs in the consideration of corporate tax savings through debt financing, which is taken into account in tax due diligence but not in FDD. Apart from this, the company valuation can essentially be based on the FCF determined in FDD (Pomp, 2015).

they help to identify required actions and determine their priority (Grote, 2007). Aspects from integration planning can also be incorporated into FDD. Such aspects, especially in sell-side projects, do not typically represent the "classical content of due diligence" [translated from German] (Götzen et al., 2016, p. 119), since the target is often analyzed on a stand-alone basis. Thus, the investor-specific combined case, which also takes into account the expected value contribution of the transaction, usually only plays a role in determining the upper price limit. In order to reduce the information loss between due diligence and the start of future integration measures, synergies and integration costs, especially in buy-side due diligences, are increasingly taken into account in FDD (Götzen et al., 2016). In the context of the assessment of synergies, FDD is concerned with the timing and certainty (so-called comfort degree) of realizing synergy potentials. Possible dyssynergies must also be accounted for. Also one-off and running costs for the integration have to be considered and checked for timing and comfort degree. Finally, the synergy effects and integration costs are reflected in a pro forma presentation of the financial statements. This presentation is particularly relevant for publicly listed companies, as it enables the effects of the M&A transaction to be portrayed transparently to their shareholders and lenders (Götzen et al., 2016).

2.2.6 Suitability of data analytics – A critical assessment

In order to critically assess FDD with regard to the use of data analytics, it is necessary to first evaluate the current achievement of objectives and to subsequently evaluate the potential analytics-induced improvements. As explained in Section 2.2.4.1, FDD pursues the three overarching objectives of (i) identification and consideration of risks as well as protection from risks, (ii) identification of value potentials, and (iii) negotiation and decision-making support.

In order to achieve the first two objectives, technical expertise, the availability of data, the quality of data (Lucks and Meckl, 2015), and the depth of the analyses are crucial. Technical expertise is readily available within specialized transaction teams of the large auditing companies. Often, however, data availability and data quality have been limiting factors. This is especially true for small and medium-sized targets and on the buy-side (Götzen et al., 2016; Pomp, 2015; Störk and Hummitzsch, 2017). Pomp (2015) stresses that many analyses depend on "the quantity and quality of available financial data. Quantity and quality [in turn] depend on the target company's implemented controlling instruments" [translated from German] (p. 85). He further specifies that “[i]n particular, small and medium-sized enterprises often use only rudimentary controlling instruments. In these cases, profitability analyses are sometimes only possible at an aggregated level, i.e., at the overall enterprise level” [translated from German] (Pomp, 2015, p. 85). Götzen et al. (2016) mention different reasons for the paucity of data availability among small and medium-sized companies such as (i) lack of disclosure obligations due to undercutting commercial size criteria, (ii) lack of monthly reporting as is usual for large companies, and (iii) lack of integrated financial planning, which is usually required for a future-oriented company valuation. Additionally, the reasons they give for the lower data quality include: (i) not having closing and accrual postings within monthly financial statements, which can significantly limit the informative value of monthly analyses, and (ii) the availability of important analyses as auxiliary calculations without connection to the reporting systems. Störk and Hummitzsch (2017) determine that data provision takes much more time for smaller companies that are managed by their owners. A further limitation is time restrictions (Reuer, 2005; Störk and Hummitzsch, 2017), especially on the buy-side and in auction processes (Andreas and Beisel, 2017), which require prioritizing the most important analyses. As a result, the identification of growth opportunities and synergy potentials is often neglected when placing the focus on traditional analyses. Due to a lack of insights regarding value generation, the due diligence process lacks intersections with the teams responsible for realizing value potential after the closing. Two aspects of due diligence stand in sharp contrast to each other and have an effect on the achievement of the third objective, negotiation and decision-making support: on the one hand, securing the deal by carefully identifying risks (deal issues) or even deal breakers and on the other hand, the rapid conclusion of the transaction through a quick execution of due diligence.

In recent years, however, data quality and consistency have improved, the speed of reporting has increased (Kreher and Gundel, 2018), and the availability of financial information from enterprise resource planning (ERP) systems has risen dramatically (Rauner, 2019). These developments could be an essential cornerstone for strengthening the achievement of FDD objectives. Based on the growing availability and quality of data, using data analytics solutions could further support the achievement of the three formulated objectives and could ameliorate the existing conflict between thoroughness and speed.

In the following, theoretical considerations concerning potential advantages arising from the integration of larger amounts of (also non-financial) information, as well as the use of analytics in FDD, are outlined. These considerations include both processual improvements and an increasing degree of sophistication in the analyses performed. First, the tension between thorough analyses and limited time for those investigations may be eased. The process can be accelerated through standardized analytics procedures and (partial) automation (Beckmann et al., 2019; Rauner, 2019). In particular, common analyses such as revenues and profitability by countries, price-volume analysis, and transformation of the balance sheet into the net asset format, offer room for standardization (Rauner, 2019). The increasing data granularity, but also the availability of a new toolkit, has led to a considerable improvement in the depth of analysis (Rauner, 2019). Furthermore, if manual efforts and routine tasks are decreased (see Harder, 2018 for the auditing domain), either the spending on service providers could be reduced or the increased speed could leave more time for the interpretation of, and deep dives into, areas of particular interest. Since FDD requires more judgement than the external auditing domain (e.g., for normalizations or adjustments), these interpretations and deep dives can be expected. Rauner (2019) provides supporting evidence for the increased time available for interpretation. Additional benefits include reducing latency when processing large amounts of data (Rauner, 2019) and improving data quality (Beckmann et al., 2019; Rauner, 2019). For example, data from different sources can be reconciled on the basis of comprehensive data models, which helps identify inconsistencies and lowers error susceptibility (Rauner, 2019). The increased data transparency creates confidence among bidders, so that purchase price discounts due to uncertain financial information can be avoided (Rauner, 2019). Employing a comprehensive data model also facilitates the integration of trading updates and therefore leads to further time saving in the FDD process (Rauner, 2019). In addition, the flexible slicing and dicing of modern analytics solutions makes it feasible to react quickly to ad hoc requests, whose results can be illustrated using data visualization tools (Beckmann et al., 2019). In carve-out transactions, the considerable flexibility offered by these tools increases transparency through the bottom-up aggregation of the newly defined object for sale's financial information for which no previous, separate reporting exists (Rauner, 2019). The analysis of larger amounts of more granular data and the enrichment through external data sources, combined with analytics capabilities that allow for more sophisticated analyses, could lead to an increase in quality of the findings (Mackenstedt, Menze, and Werner, 2018).

Connecting traditional accounting and financial data with additional information (e.g., big data sources) can facilitate the identification of strengths, weaknesses, opportunities, risks, and value drivers. It thus reduces the information asymmetry between the target and potential buyers (Beckmann et al., 2019; Mackenstedt et al., 2018; Rauner, 2019). Since buyers have the incentive to close the information gap, they should be interested in data-related insights. The integration of more advanced analyses into deal negotiations allows for more fact-based argumentation and could consequently reduce the need for discussions. Finally, positive spin-off effects on related work streams (especially company valuation, post-merger integration, and other due diligence disciplines) can be expected through the transfer of more standardized data formats from the FDD discipline. All these potential improvements may ultimately lead to higher M&A transaction success rate.

Despite wide ranging process improvements and an increasing degree of sophistication of the analyses because of analytics software, potential downsides must also be considered. In particular, Rauner (2019) highlights the increased effort for data preparation in the early stages of the FDD process. He emphasizes the necessity of technical skills, which he finds to be limited in his assessment of consultants' capabilities.

Thus, certain conditions must be fulfilled for the benefits to outweigh these drawbacks. Rauner (2019) considers analytics tools to be useful only in situations with a (i) sufficient data availability, particularly in (ii) sell-side transactions that offer good access to the target's ERP and controlling systems. Additionally, (iii) complex transactions, especially carve-outs, are well-suited to employing analytics tools. Finally, (iv) investors' requirements and expectations, (v) the envisaged timeline, and (vi) the FDD team's competencies are relevant determinants when deciding whether or not to apply analytics software. For buy-side clients, Beckmann et al. (2019) deem data analytics to be particularly suitable in (vi) exclusivity situations or for transaction phases with a limited number of bidders.

2.3 Summary

There are different views of the M&A process that result in various process models. Most M&A process frameworks are divided into three stages: preparation, transaction, and integration. Due diligence mainly takes place in the transaction phase of a potential M&A deal. However, the presentation of the entire FDD process in the literature is currently unsatisfactory. On the one hand, some publications consider all phases of the process, but without the necessary depth. On the other hand, some studies deal in detail with the FDD's core, the analysis phase, but mostly disregard other important process stages. However, a holistic and simultaneously profound knowledge of the FDD process is necessary to deal with the research questions. This dissertation therefore combines existing approaches within a holistic process framework and a detailed description of the entire FDD process. The typical process is divided into three phases: preparation, analysis, and reporting. In the preparation phase, project coordination and data (room) preparation take place. The analysis phase, which forms the core of due diligence, consists of reviews of historical, current, and planned profitability, balance sheet, and cash flows. In particular, the analyses derive pro-forma adjusted, normalized earnings, balance sheet, and FCF that serve as the basis to validate the business plan. In the reporting phase, the FDD report as final project deliverable is shared with the relevant stakeholders.

In addition to the literature-based compilation of the outlined FDD process model, the existing literature is expanded on a second point: The objectives pursued by FDD, which so far have only been loosely described in various studies, are systematically bundled and defined more precisely in this dissertation. Based on the three objectives formulated, (i) identification and consideration of risks as well as protection from risks, (ii) identification of value potentials, and (iii) negotiation and decision-making support, the suitability of using analytics in FDD is examined.

Based on the increasing availability, granularity, and quality of data, the integration of analytics software appears to be an extremely promising approach to improving the FDD process and its results. The anticipated processual and content-related benefits appear highly conducive to achieving the goals of FDD. However, the concrete benefits of using analytics tools depend on various circumstances such as data availability, the initiator of due diligence (sell-side vs. buy-side), the exclusivity of negotiations, the transaction's complexity (e.g., high in carve-out deals), requirements and expectations of investors, time restrictions, and the competencies of the FDD team. Moreover, the use of analytics software compared to traditional tools is related to a few, but considerable downsides such as requiring a longer time for data preparation. Consequently, it must also be examined under which conditions the use of analytics is particularly appropriate in relation to its use in the FDD process, how well it is already being adopted, and what factors are still hampering acceptance despite the benefits (see research questions in Section 1.2).

In order to answer these research questions, the application of analytics in other finance and accounting domains (Chapter 3) and the adoption of new technologies by audit firms (Chapter 4) will first be investigated. With the knowledge gained about different use cases, the actual and possible future use of analytics in FDD is examined. In this context, a qualitative analysis is carried out using semi-structured expert interviews (Chapter 5). Finally, the findings are empirically tested with the help of a questionnaire (Chapter 6).

3 Data analytics and big data – Definitions and use

This chapter provides an overview of business intelligence (BI), data analytics, and big data. After an introduction to the evolution of BI and an outline of a representative BI environment, the analytics component of that environment is depicted in greater depth (Section 3.1). The next section focuses on big data, which has been prime for the further development of analytics (Section 3.2). In a subsequent literature review, the current use of data analytics and the inclusion of big data into analyses in finance and accounting domains are scrutinized. The opportunities to transfer the proposed use cases to FDD are briefly discussed (Section 3.3). Finally, the chapter concludes with a short summary (Section 3.4).

3.1 Business intelligence and data analytics

As Evans (2016) outlines, "[a]nalytical methods, in one form or another, have been used in business for more than a century" (p. 5). The modern evolution of analytics began with the invention and development of computers in the mid of the 20th century and led to the introduction of BI (Evans, 2016). Ever since, the analytics aspect of BI has made continual progress, moving from descriptive to more advanced, future-oriented predictive analytics or even prescriptive analytics. This section details the development of BI and depicts the embedded role of analytics and how its importance in research has increased in recent years (Section 3.1.1). It also defines and classifies data analytics (Section 3.1.2).

3.1.1 Business intelligence

After presenting a historical view of BI, a working definition is formulated. Later, the different components of a generic BI environment are briefly explained and the role of analytics is elucidated.

3.1.1.1 Definition of business intelligence

In 1958, the German computer scientist Hans Peter Luhn was the first to portray BI systems as a means to "accommodate all information problems of an organization" (Luhn, 1958, p. 314). From that time onwards, various concepts with slight alterations in notion and scope have been proposed for information systems (IS)-enabled decision support. The most commonly known concepts include management information systems (MIS) (Gallagher, 1961), decision support systems (DSS) (French and Turoff, 2007), and executive information systems (EIS) (Rockart and Treacy, 1980).

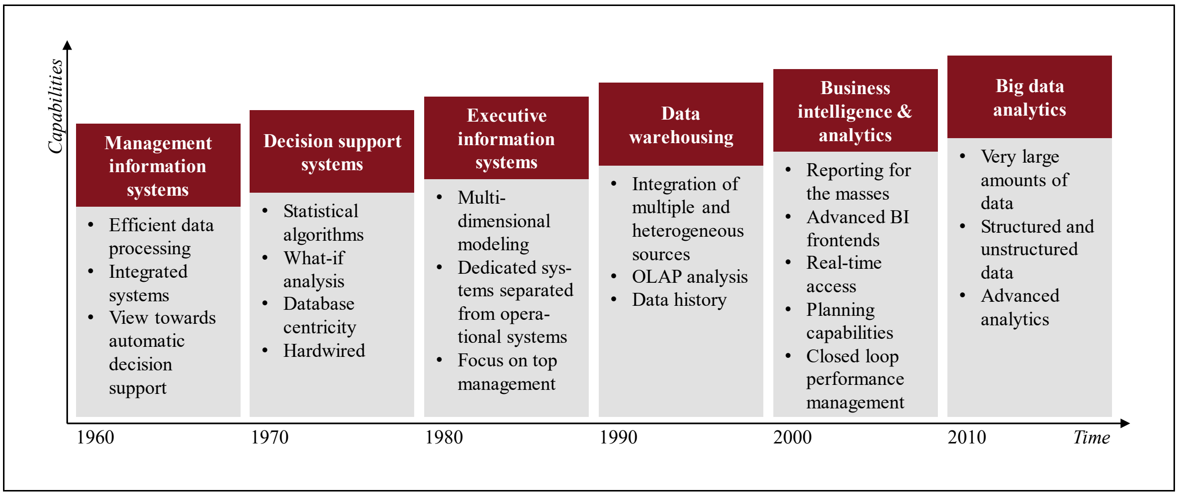
MIS were created in the 1960s to support strategic and tactical decisions (Gallagher, 1961). In the subsequent decade, DSS were developed to address a broader spectrum of decision support. DSS are systems based on detailed, problem-specific data analysis models and databases that interactively support decision-makers in semi-structured decision problems (Davis and Olson 1985; Laudon and Laudon 2006). EIS, on the other hand, are explicitly aimed at business management and decision support in the context of planning and management tasks (Rockart and Treacy 1980). A commonality of all these systems is that they enable or improve the ability to make decisions within certain management processes. The modern understanding of BI builds upon these concepts (Negash and Gray, 2008).

In the early stage of development, IS that aimed at decision support were narrowly defined and system-focused. Since its inception, however, the term has evolved from a collective term for a more technology-driven approach based on data analysis, reporting, and query tools (Anandarajan, Anandarajan, and Srinivasan, 2004) to a generic term for an integrated sociotechnical infrastructure for decision support (Baars and Kemper 2008; Hallikainen, Merisalo-Rantanen, Syvaniemi, and Olivera, 2012). Herschel (2010) summarizes the broad view on BI: “Today, the practice of BI clearly employs technology. However, it is prudent to remember that BI is also about organizational decision-making, analytics, information and knowledge management, decision flows and processes, and human interaction” (p. i). The broad scope of BI has led to a plethora of definitions; however, “there is no universally accepted definition of BI” (Wixom and Watson 2010, p. 14).[55] This dissertation follows Wixom and Watson’s (2010) comprehensive definition of BI as a “broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions” (p. 14), which includes the components, activities, and objectives of BI. Consequently, this thesis extends its focus beyond merely the technological aspects by also exploring *how* analytics technology is used in FDD.

The evolution from MIS towards BI, and even big data analytics, which is introduced at a later stage after presenting the concept of big data (see Section 3.2.2), is depicted in Figure 3.1.

[55] See Zeides (2010) for a discussion of different definitions of the term BI.

Figure 3.1: History and evolution of business intelligence



Source: Own illustration based on Mädche (2014)

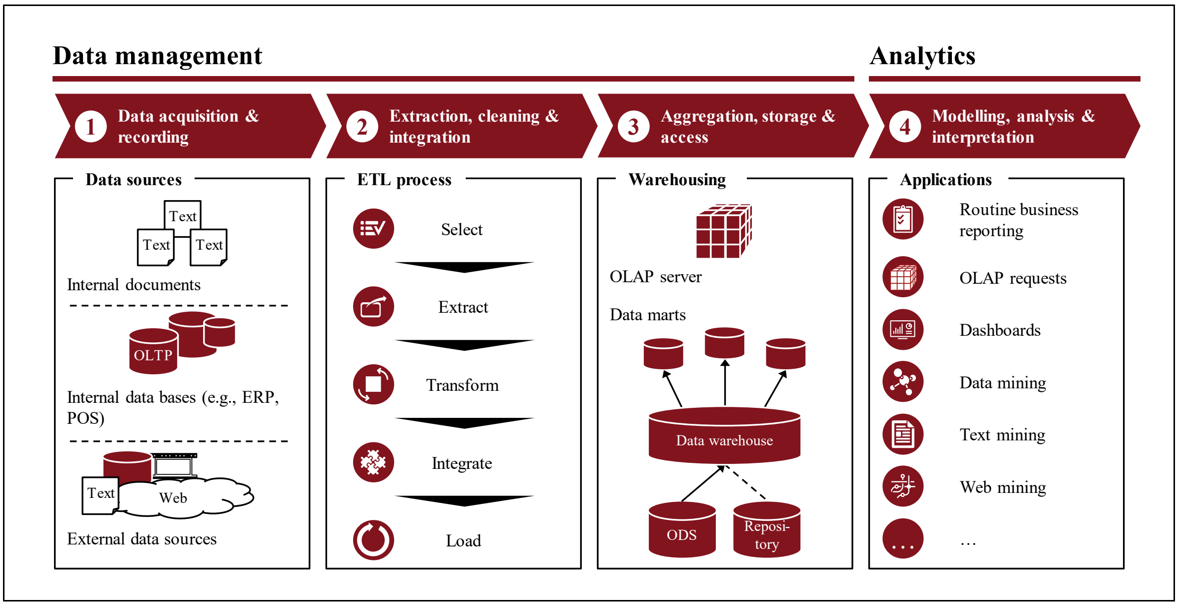
3.1.1.2 Constitution of a business intelligence environment

BI environments vary across different organizations. For the sake of simplification, Wixom and Watson (2010) present a generic, comprehensive BI environment. For exemplification purposes, the visualization is enriched by further elements from Gandomi and Haider (2015), Müller and Lenz (2013), and Turban, Sharda, and Delen (2014) (see Figure 3.2). The BI architecture and its components follow the process from data collection to ultimate decision-making by "gathering data from source systems, storing the data, and accessing and analyzing the data using BI technologies and applications" (Wixom and Watson, 2010, p. 14). The first component of BI systems are therefore data sources, which can be both internal (mostly transactional) and external and possess structured as well as unstructured data. In the data integration, heterogeneous data from different source systems is extracted, transformed, and loaded (ETL process)[56] into an operational data storage or data warehouse (DWH), respectively (Müller and Lenz, 2013). The DWH is the central component of most BI architectures as it usually integrates, consolidates, aggregates, and structures data from a large number of source systems for analytical purposes (Inmon, Strauss, and Neushloss, 2008; Kimball, Ross, Thornthwaite, Mundy, and Becker, 2008). The information collected and stored in the DWH is made available to users for analytical

[56] The order depends on the infrastructure and can also be extract, load, and transform (ELT process) (Alles and Gray, 2016). In the extraction step, data from a database is read. In the transformation step, the extracted data is converted from its previous form into the target form through filtering, harmonization, enrichment, and aggregation. In the load step, the data is put into the DWH.

purposes either directly or via data marts.[57, 58] In the subsequent analysis step, automated analysis tools and (standard) reporting systems are employed. In addition, online analytical processing (OLAP) is used as a multi-dimensionally organized access technique for the data stock (Codd, Codd, and Salley, 1993).[59] Analysis and visualization can be conducted by business performance management (BPM) systems and its scorecards and dashboards (Chen, Chiang, and Storey, 2012). Beyond these well-established analysis approaches, “statistical analysis and data mining techniques are adopted for association analysis, data segmentation and clustering, classification and regression analysis, anomaly detection, and predictive modeling in various business applications” (Chen et al., 2012, p. 1166). Analysis results from all of these components are used for their ultimate purpose: decision-making support.

Figure 3.2: Generic business intelligence environment



Source: Own illustration based on Gandomi and Haider (2015), Müller and Lenz (2013), Turban et al. (2014), and Wixom and Watson (2010)

[57] Müller and Lenz (2013) describe data marts as “small [d]ata [w]arehouses” (p. 21), i.e., excerpts from the DWH, which have a special application. Since they usually only contain a subset of the DWH, data marts offer the advantage of faster data retrieval. Moreover, they provide users with a flexible way of customizing their data requests.

[58] In Figure 3.2, a hub-and-spoke DWH (with dependent data marts drawn from the DWH) is shown to illustrate both the DWH and data marts to the reader. Three alternative options include a data mart-centric approach (with independent data marts), an enterprise DWH (with centralized integrated data and direct access to the DWH), and a virtual, distributed, federated approach (with neither a DWH nor data marts) (Turban et al., 2014).

[59] Typical OLAP operations for (ad hoc) analysis include drilling up or down, slicing and dicing, pivoting/rotating, and drilling across or through.

3.1.2 Data analytics

As outlined in the previous section, BI incorporates a broad spectrum of technologies, applications, and processes for gathering, storing, accessing, and analyzing data. While the BI research community has devoted itself over many years to the development of sustainable technological and organizational concepts of data management (see left-hand side of Figure 3.2), the focus has in recent times increasingly shifted towards the methods and applications of (advanced) data analysis (see right-hand side of Figure 3.2) (Gluchowski, 2016). In line with this trend, recent studies in the finance and accounting domain have concentrated on the different technologies available for the data analysis step and their respective fields of application. This thesis follows the path of previous literature and has the topic of *data analytics* as its core. Nonetheless, a comprehensive understanding of all technological components of a BI environment is essential to evaluate different options for the use of data analytics. Put differently, to understand how analytics can be used in FDD, an initial evaluation of its use of basic data management functions (e.g., ETL process) is needed. In the following section, data analytics will be defined and classified along three dimensions.

3.1.2.1 Definition of data analytics

In the late 2000s, business analytics was introduced as a key analytical component in BI (Davenport, 2006). Business analytics as defined by Davenport and Harris (2007) is “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions. The analytics may be input for human decisions or may drive fully automated decisions. Analytics are a subset of […] business intelligence.” (p. 7). Evans (2016) expands upon the above definition by adding the use of IT and notes that analytics is supported by various tools, statistical software, and BI suites.

In contrast to business analytics, data analytics has a larger scope due to its less-specific business focus. However, as this study makes use of both terms in a business-related context, business analytics can be seen as a synonym for data analytics for the purpose of this thesis. This procedure is in line with prior literature (e.g., Evans, 2016; Gluchowski, 2016; Holsapple et al., 2014).

Analytics can be conceptualized with the three distinct, albeit complementary dimensions of domain, orientation, and technique, which help to understand its scope (Holsapple et al., 2014). Domain “refers to subject fields in which aspects of analytics are being applied" (Holsapple et al., 2014, p. 132), i.e., it links to the context or environment. Orientation describes the direction of thought or the outlook of analytics. The most common classification of orientation is a three-fold taxonomy consisting of descriptive, predictive, and prescriptive analytics (Delen and Demirkan, 2013; Evans, 2016; Liberatore and Luo, 2011; Lustig, Dietrich, Johnson, and Dziekan, 2010). Lastly, "techniques refer to the analytical processes of the domain and orientation" (Appelbaum et al., 2017, p. 6) and can be differentiated along multiple criteria (see Section 3.1.2.4).

3.1.2.2 Domain-based classification

In a business context, the domains and sub-domains of data analytics include numerous traditional business administration disciplines. According to Holsapple et al. (2014), these domains include: "marketing, human resources, business strategy, organization behavior, operations, supply chain systems, information systems, and finance" (p. 132). Within each of these domains, analytics are commonly applied to various subtopics (e.g., customer analytics as part of marketing analytics) (Holsapple et al., 2014).

This dissertation focuses on the finance and accounting domain. Prior literature on the application of data analytics in these areas is presented in Section 3.3.4.

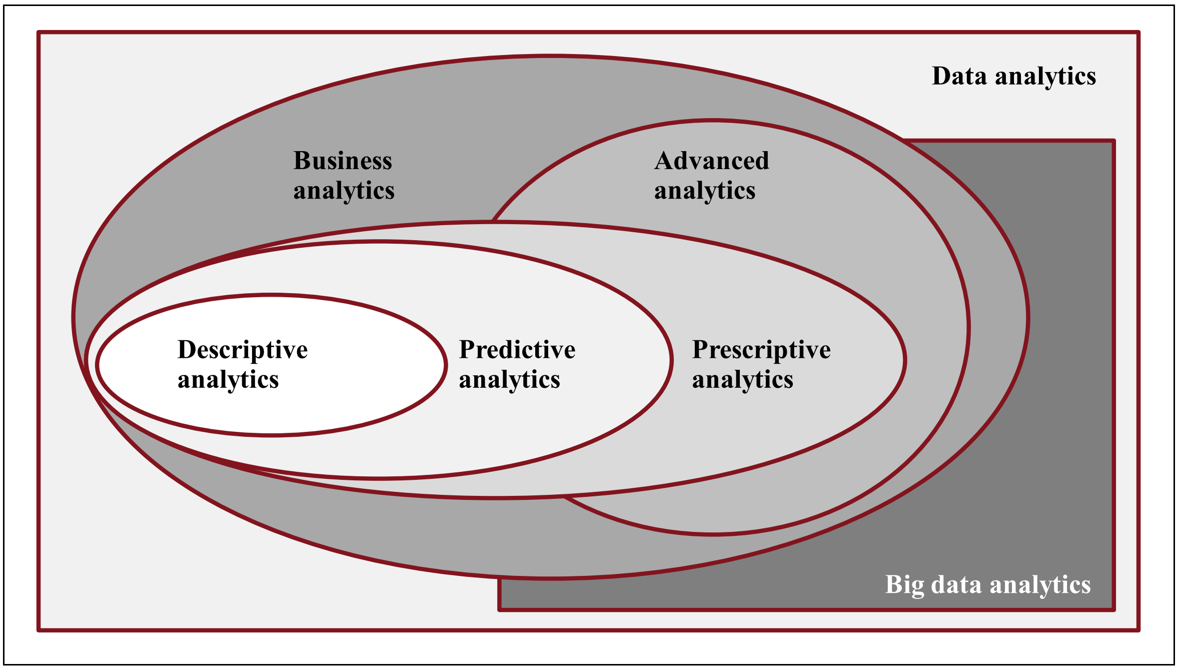
3.1.2.3 Orientation-based classification

As already outlined, the most frequently applied taxonomy to differentiate directions of thought is the distinction made between descriptive, predictive, and prescriptive analytics (Delen and Demirkan, 2013; Evans, 2016; Liberatore and Luo, 2011; Lustig et al., 2010) (see Figure 3.3).[60] Backward-looking descriptive analytics has always been a significant component of BI systems and includes such applications as dashboards, scorecards, and data visualization (Sivarajah et al., 2017; Watson, 2014). In contrast, the forward-looking predictive and prescriptive analytics, summarized under the umbrella term advanced analytics, represent an extension of traditional BI

[60] According to Spiess, T'Joens, Dragnea, Spencer, and Philippart (2014) diagnostic or inquisitive analytics also fall under the spectrum of descriptive analytics and are viewed as a fourth form of analytics by some researchers (e.g., Chahal, Jyoti, and Wirtz, 2019; Sivarajah, Kamal, Irani, and Weerakkody, 2017).

(Chahal et al., 2019). Their derivation of predictive models clearly exceeds the capabilities of mostly explorative and past-oriented data analysis in BI (Chamoni and Gluchowski, 2017).

Figure 3.3: Orientation-based classification of analytics



Source: Own illustration based on Gluchowski (2016)

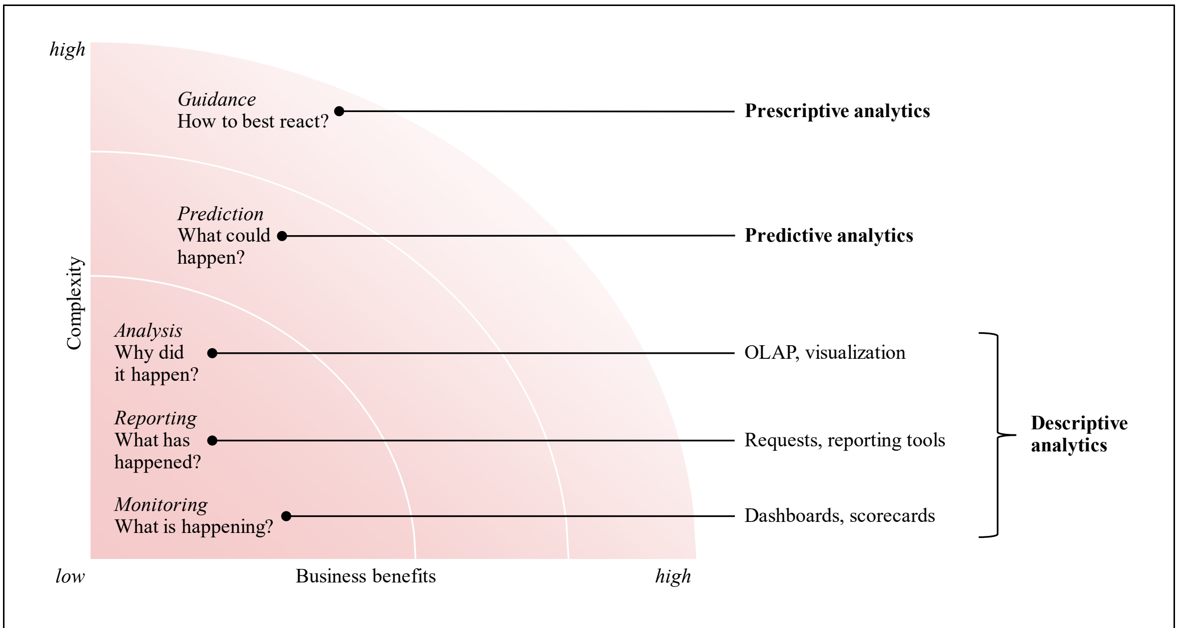
As the simplest form of analytics, descriptive analytics involve basic statistical methods (e.g., mean, median, mode, standard deviation, variance) (Rehman, Chang, Batool, and Teh, 2016) and visualization techniques (Evans, 2016). Historical data is used to identify patterns and create management reports by means of descriptive analytics applications (Assunção, Calheiros, Bianchi, Netto, and Buyya, 2015; Chong and Shi, 2015).

As outlined above, predictive analytics differ from the purely backward-looking descriptive analytics in the time frame of their application. Predictive analytics employ historical and current data to feed forecasts and forward-facing statistical models (Waller and Fawcett, 2013). This type of analytics uses methods and technologies that can uncover salient patterns in large databases and can be used to make forecasts about future events and conditions (Gluchowski, 2016). The methods applied in predictive analytics include data mining, predictive modeling, machine learning, forecasting, and simulation (Evans, 2016; Jou and Ng, 2013; Minelli, Chambers, and Dhiraj, 2013).

Prescriptive analytics, the latest evolutionary stage of analytics, can be defined as “[a] set of mathematical techniques that computationally determine a set of high-value alternative actions or decisions given a complex set of objectives, requirements, and constraints, with the goal of improving business performance” (Lustig et al., 2010, p. 12). In addition to the prospective view of predictive analytics, prescriptive analytics determine the optimal action for benefiting promptly from the prediction (Basu, 2013). For that reason, Appelbaum et al. (2017) describe prescriptive analytics as “an optimization approach” (p. 32), meaning mathematical simulation models or operational optimization models with a prescriptive orientation that take into account business rules, constraints, and thresholds, discern uncertainties and provide mitigation strategies (Appelbaum et al., 2017). Many of these models revert to techniques from operations research such as linear, non-linear, or stochastic optimization (Chamoni and Gluchowski, 2017).

The different evolutionary stages of analytics and their spectra are summarized in Figure 3.4 and Figure 3.5, respectively.

Figure 3.4: Evolution of analytics



Source: Own illustration based on Lehmann (2012)

Figure 3.5: Spectrum of analytics

	Descriptive analytics	Predictive analytics	Prescriptive analytics
Direction of analysis	• What and when did it happen? • How much is impacted and how often does it happen? • What is the problem?	• What is likely to happen next? • What if these trends continue? • What if?	• What is the best answer? • What is the best outcome given uncertainty? • What are significantly differing and better choices?
Key techniques	• Simple calculations • Statistics	• Data mining • Predictive modelling • Machine learning • Forecasting • Simulation	• Constraint-based optimization • Multi-objective optimization • Global optimization

Source: Own illustration based on Minelli et al. (2013)

In recent years, the questions raised in descriptive, predictive, and prescriptive analytics, as exemplary illustrated in the above figures, are increasingly solved autonomously. This technological evolution of analytics is called autonomous analytics and it refers to the employment of artificial intelligence (AI) and cognitive technologies with the purposes of creating and enhancing models and learning from data, all with substantially less human involvement (Davenport and Harris, 2007). Although this form of analytics possesses an autonomous character, it does not have a different orientation than the previous three forms and is thus commonly not handled separately.

3.1.2.4 Technique-based classification

Techniques can be differentiated along multiple distinctions such as (i) qualitative, quantitative, and hybrid (Appelbaum et al., 2017; Cody, Kreulen, Krishna, and Spangler, 2002; Davenport, Harris, and Morison, 2010; Davenport and Kim, 2013), (ii) dealing with structured, semi-structured, and unstructured data (Appelbaum et al., 2017; Inmon and Nesavich, 2008), (iii) being of a confirmatory or an explorative nature (Appelbaum et al., 2017; Praseeda and Shivakumar, 2014), (iv) being deterministic or statistical (Appelbaum et al., 2017), or (v) having specific mechanisms used for analytics (e.g., approaches to data mining) (Fong, Hui, and Jha, 2002; McCue, 2006). Appelbaum et al. (2017) provide a classification of 28 common techniques of analytics into the first four aforementioned categories.

In the past, the most advanced business analytics techniques had their origins in statistical data analysis. For that reason, the most traditionally used techniques in the accounting domain are quantitative, statistical methods based on structured data (Appelbaum et al., 2017; Appelbaum et al., 2018). By contrast, the latest research has started incorporating methods from machine learning, AI, deep learning, text mining, and data mining (Appelbaum et al., 2018).

In the descriptive analytics field, visualizations (e.g., in the forms of dashboards and menus) are frequently used in business practice (Dilla, Janvrin, and Raschke, 2010). Reports are another typical component (Davenport and Kim, 2013) and include format elements such as pie charts, heat maps, or geographical maps, to facilitate quick understanding of the results of analysis. Most of the techniques used in descriptive analytics rely on mature commercial technologies, particularly relational database management systems, DWH, ETL, OLAP, and BPM (Chaudhuri, Dayal, and Narasayya, 2011).

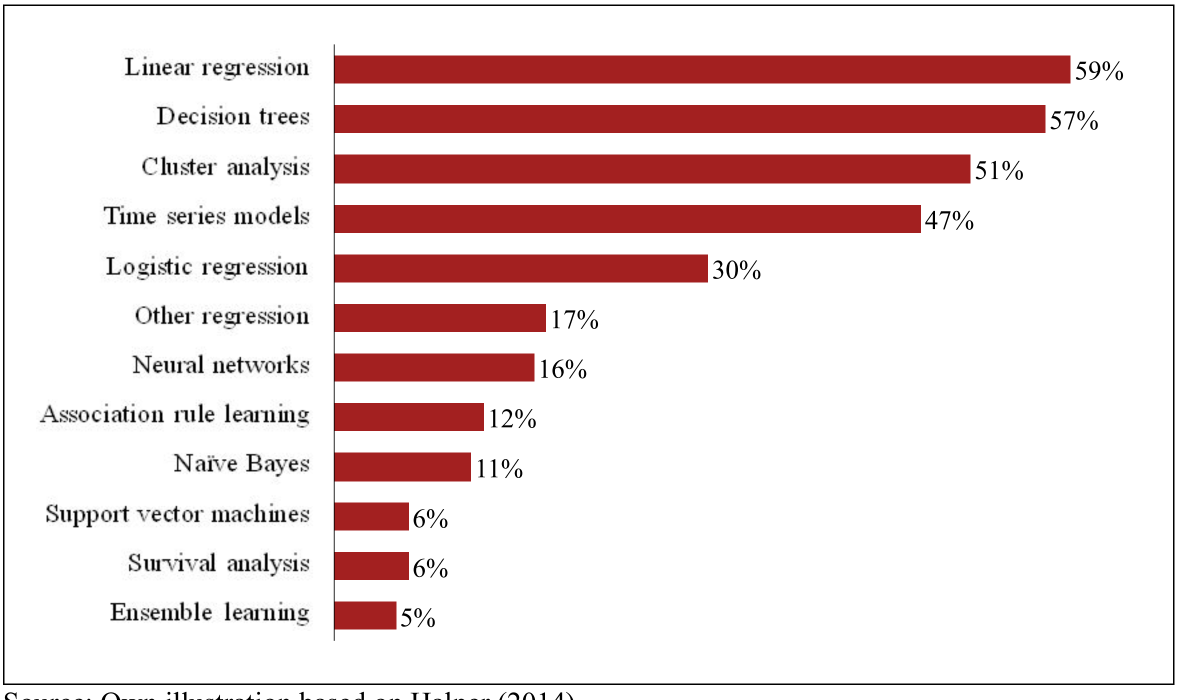
Predictive analytics encompass a broad spectrum of techniques, which include data mining, predictive modeling, machine learning, forecasting, and simulation (Evans, 2016; Jou and Ng, 2013; Minelli et al., 2013). The largest repertoire of techniques stems from data mining. Han, Kamber, and Pei (2012) define data mining as "the process of discovering interesting patterns and knowledge from large amounts of data" (p. 8), which leverages an extensive toolset (Kantardzic, 2011).[61] The different data mining techniques are primarily concentrated in four building blocks: association pattern mining (e.g., brute force and apriori algorithms, enumeration trees, recursive suffix-based pattern growth methods), clustering (e.g., k-means algorithms), outlier analysis (e.g., distance-based quantification, dimensionality reduction), and classification (e.g., decision trees, support vector machines, neural networks, Naïve Bayes, regression modeling) (Aggarwal, 2015). Deviating from this taxonomy, prior literature has partially regarded regression as a field in its own right and separate from the classification technique (Chen et al., 2012; Kantardzic, 2011). Some researchers also view summarization (e.g., visualization, report generation) as a separate category (Kantardzic, 2011). In addition to data mining techniques, which primarily uncover previously unknown data patterns, forecasting (e.g., time-series analysis), simulation (e.g., Monte Carlo simulation), predictive modeling, and machine learning techniques also serve to predict the future. While these fields have large overlaps, they differ

[61] Data mining is also known as "knowledge discovery from data" (Han et al., 2012, p. 1).

slightly in their focus. For instance, forecasting assumes identified trends will continue, while simulation takes a set of possible scenarios into account (Praseeda and Shivakumar, 2014).

In her survey of 126 practitioners who actively use predictive analytics in their organizations, Halper (2014) finds that linear regression, decision trees, and cluster analysis constitute the most commonly applied techniques in practice (see Figure 3.6).[62] While numerous data mining algorithms had already been developed by the late 1980s, their implementation was slow (Chen et al., 2012). Today, not only have most of these data mining algorithms become popular and have been incorporated into commercial and open source software solutions (Witten, Frank, and Hall, 2011), but analytics applications have also become more user-centric and consumer-friendly (Jou and Ng, 2013).

Figure 3.6: Most applied predictive analytics techniques



Source: Own illustration based on Halper (2014)

[62] The survey was conducted across various industries with the largest group of participants working in consulting and professional service organizations (19%). This group is also the focus of this dissertation.

Prescriptive analytics rely on similar techniques to predictive analytics,[63] but combine them with optimization approaches (Appelbaum et al., 2018). The results of predictive techniques are enriched by mathematical simulation models or operational optimization models that take into account business rules, constraints, and thresholds to identify the optimal course of action and its effects on a given problem (Appelbaum et al., 2017; Appelbaum et al., 2018). These optimization models include linear and non-linear optimization as well as integer optimization (Evans, 2016). However, the integration of corresponding algorithms into commercial software solutions, and consequently the practical use of prescriptive analytics, lags substantially behind that of predictive analytics. The difference between the technological evolution and adoption of predictive and prescriptive analytics is underscored by the so-called hype cycle (Hare and Schlegel, 2019).

3.2 Big data

Although the relational and OLAP databases of traditional BI systems are used to analyze static snapshots of mostly numerical, very structured data, today's data landscape requires advanced forms of analytics (Jou and Ng, 2013). The increasing availability of data, paired with growing storage and computation capacity, has fueled the rise of advanced (i.e., predictive and prescriptive) analytics (Manyika et al., 2011). For example, Minelli et al. (2013) explain that the use of many different data sources (e.g., traditional internal data enriched by external data sources) "make[s] the predictions more accurate and meaningful" (p. 71). However, the increasing amount of data is accompanied by increasing data complexity. This development is best described as *big data*. This section defines the phenomenon of big data, classifies big data along two dimensions (Section 3.2.1), and compares the analysis of big data to the analysis of traditional data (Section 3.2.2).

3.2.1 Definition and classification of big data

As described by Alles and Gray (2016), there is no consistent definition for big data because while "some [b]ig [d]ata definitions focus on the dimensions or characteristics […] other definitions focus more on examples of the contents" (p. 48). To provide a comprehensive view of big data, both the characteristics and content examples are presented.

[63] Appelbaum et al. (2017), for example, characterize all techniques as either descriptive or both predictive and prescriptive.

3.2.1.1 Characteristic-based classification

From the characteristics perspective, the term big data is commonly described using the five V's of volume, variety, velocity, value, and veracity (Fasel and Meier, 2016). While volume, variety, and velocity build the core of the initial synopsis of big data (Gillon, Aral, Lin, Mithas, and Zozulia, 2014; Goes, 2014; Hashem et al., 2015; Lycett, 2013; McAfee and Brynjolfsson, 2012), value (Hashem et al., 2015; Lycett, 2013) and veracity (Gillon et al., 2014; Goes, 2014) have subsequently been added.

Volume describes the amount of data generated by different data sources. The data stock is considerable and lies in the terabyte to zettabyte range (Fasel and Meier, 2016).[64] However, there is no threshold that defines whether data is big. Vasarhelyi et al. (2015) underline that "[w]hether a dataset has big volume is relative and depends on the capabilities of the information system. These capabilities are usually categorized along the dimensions of storage and processing" (p. 382). Thus, both the storage and processing of large amounts of data are essential as more data leads to more accurate models (Lycett, 2013).

Variety refers to the different types of data collected (Shim, French, Guo, and Jablonski, 2015). For example, these can be texts, images, videos, or position data from social networks, mobile devices, and/or sensors (Fasel and Meier, 2016; Hashem et al., 2015). The variety of different data types leads to different content formats, which can be either structured, semi-structured, or unstructured (Fasel and Meier, 2016).

Velocity characterizes the rate of data generation (Shim et al., 2015) and transmission (Hashem et al., 2015). This speed allows for the analysis of data streams in (near) real-time (Fasel and Meier, 2016). Velocity also reflects the continuous change of data content (Hashem et al., 2015).

Value denotes collected information's worth to the corporation (Shim et al., 2015). The factor critical to extracting valuable information from the data collected is the corporation's capabilities (e.g., personnel, technical infrastructure) (Fasel and Meier, 2016). According to Hashem et al. (2015), value is the most important dimension of big data.

[64] The conversion of data size from bytes into larger units is performed as follows: kilobyte = 10^3 bytes, megabyte = 10^6 bytes, gigabyte = 10^9 bytes, terabyte = 10^{12} bytes, petabyte = 10^{15} bytes, exabyte = 10^{18} bytes, zettabyte = 10^{21} bytes.

Veracity is an indicator of the degree of uncertainty (Bendler, Wagner, Brandt, and Neumann, 2014) and integrity (Shim et al., 2015) of the data collected. Factors that can influence veracity include the accuracy, truthfulness, and precision of the data (Shim et al., 2015). Since extensive data compilations do not guarantee better evaluation quality, different data quality must be taken into account in the data assessment and analysis (Fasel and Meier, 2016).

Table 3.1 summarizes the five dimensions of big data described above and provides examples as well as challenges for each.

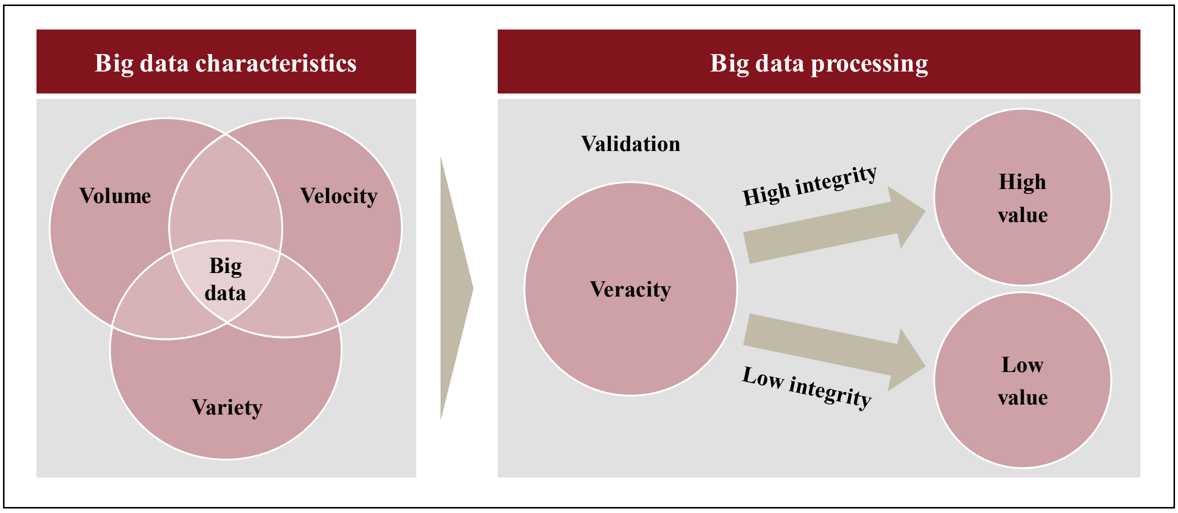
Table 3.1: Characteristic-based classification of big data

Characteristic	Description	Examples	Challenges
Volume	**Size** of data	• Scale of data: ranging from terabyte to zettabyte	• Data storage • Data acquisition • Data processing • Performance • Cost
Variety	**Complexity** of data through different types and formats	• Different types of data: text documents, web and social media, transactional, sensor, geolocational/geospatial, audio/voice, image, video • Different formats of data: unstructured, semi-structured, structured	• Heterogeneity of data • Diverse, dissimilar forms
Velocity	**Speed/rate** of data generation and transmission	• Analysis of streaming data: batch processing, real-time processing, streaming processing	• Slow and expensive nature of data processing
Value	**Worth** of collected information	• Critical factors for value extraction: corporation's capabilities such as personnel and technical infrastructure	• Revenue impact • Operational cost impact • Customer impact
Veracity	**Quality/accuracy** of data and its potential use for analysis	• Uncertainty of data: increasingly complex data structure, inconsistency in large data sets	• Accuracy of data • Reliability of data sources • Context within analysis • Inaccuracy, latency, subjectivity

Source: Own illustration based on Saggi and Jain (2018)

Figure 3.7 illustrates the interrelations of all five dimensions of big data. Shim et al. (2015) classify the five V's of big data into two subgroups: big data characteristics and big data processing. Only after big data, as characterized by its volume, variety, and velocity, has been processed, can its veracity and value become apparent and reveal whether the data serves to extract knowledge from it (Shim et al., 2015).

Figure 3.7: Interrelations between the five dimensions of big data



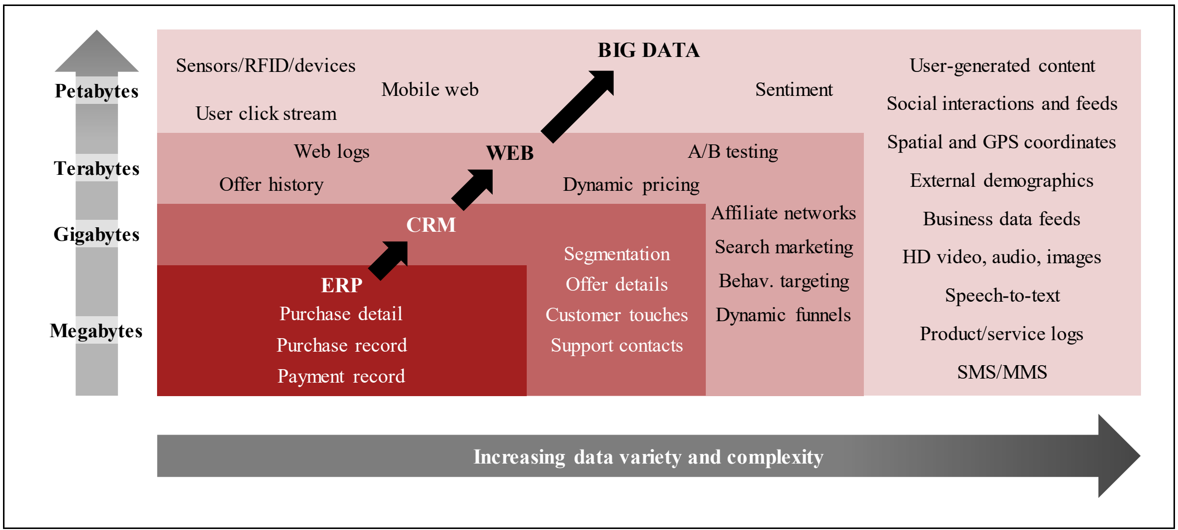
Source: Own illustration based on Shim et al. (2015)

3.2.1.2 Content-based classification

While big data can be well classified by its characteristics, a complete content-based classification is difficult to achieve due to the almost inexhaustible diversity of data. For that reason, Alles and Gray (2016) state that content-based definitions "focus more on examples" (p. 48) (see Section 3.2.1).

The graphical illustration of an extensive set of big data content examples in Figure 3.8 depicts the large variety of data. For the finance and accounting domain, Alles and Gray (2016) explain that big data can include a "mix of traditional structured financial and non-financial data, logistics data, sensor data, e[-]mails, telephone calls, social media data, blogs, as well as other internal and external data" (p. 48). Further examples are discussed in Section 3.3.3.

Figure 3.8: Content examples of big data



Source: Own illustration based on Conolly (2012) cited in Alles and Gray (2016)

3.2.2 Big data analytics

It becomes increasingly challenging for traditional architectures and infrastructures to handle large amounts of heterogeneous, unstructured data within an acceptable time and within given resource boundaries as the pace of data generation exponentially increases (Chong and Shi, 2015). The efficient value extraction from such data therefore requires new tools and methods specialized for big data storage, integration, processing, and analysis, which is brought together with the term *big data analytics* (Chong and Shi, 2015; Russom, 2011).

To overcome the challenges of traditional relational databases, technical solutions for parallel processing of queries across an entire network of servers have been established (Fasel and Meier, 2016; Mädche, 2014). The most prominent examples include so-called not only SQL (NoSQL) technology and the open source solution Apache Hadoop, which is often linked to a MapReduce processing algorithm (Fasel, 2016; Ferrera, De Prado, Palacios, Fernandez-Marquez, and Serugendo, 2013; Mädche, 2014; Saggi and Jain, 2018; Shim et al., 2015). Apache Hadoop has led to the development of a plethora of extensions for big data processing (e.g., Sawzall, Apache Flume, Apache Pig, Apache Hive, Jaql, and Cascading), which cover a broad range of users and skills (Ferrera et al., 2013; Shim et al., 2015).

3.3 Use in finance and accounting – A literature review

After outlining the theoretical background of big data and data analytics, this section covers the use of both subjects in the finance and accounting domain as presented in prior literature.

As literature on big data and data analytics in the M&A process in general and FDD in specific is especially limited, recourse is made to adjacent literature from other research veins in the finance and accounting domain.[65] Using a similar approach, Gepp et al. (2018) investigate potential big data technique use cases in the auditing domain by "analyzing research conducted in related fields that have been more willing to embrace [these] techniques" (p. 3). Alles and Gray (2016) corroborate that "researchers should identify parallels […] for insights on how […] knowledge can be transferred from one domain to the other" (p. 57). Similarly, this thesis seeks potentially transferable use cases of big data and data analytics in related fields, especially those practiced by the same service firms that also conduct FDDs. The use of such data and technologies in first mover fields could subsequently be adapted to the due diligence process, thereby providing directions for the qualitative analysis.

After adjacent literature streams are selected (Section 3.3.1) and a framework for the subsequent classification is introduced (Section 3.3.2), the use cases of big data (Section 3.3.3) and data analytics (Section 3.3.4) in the respective literature veins are presented.

3.3.1 Selection of adjacent literature streams

Auditing is the domain that can be characterized as closest to FDD, is auditing.[66] There is a high degree of congruency among the many areas of investigation; for example, both auditing and FDD need to validate completeness and valuation (Grote, 2007). Both disciplines are carried out by the same service providers: audit firms (Grote, 2007). Yet, one must not forget that FDD has a stronger business orientation, a more forward-looking perspective, and its scope is more tailored to meet the requirements of potential buyers and to meet the target company's special features

[65] These topics are also still in their infancy in other literature streams. For instance, references to the term big data emerge in finance and accounting literature around 2011 (Cockcroft and Russell, 2018) and have sharply increased since 2015 (Alles and Gray, 2016).

[66] Vice versa, Alles and Gray (2016) suggest in their auditing research that certain aspects "could be derived from […] non-audit activities" (p. 57).

(Bredy and Strack, 2011; Nieland, 2002). Moreover, "due diligence is a voluntary investigation, which also extends to the annual financial statements, commissioned by the acquirer and not by the company to be audited or its controlling bodies" [translated from German] (Grote, 2007, p. 104).[67]

Besides auditing, Gepp et al. (2018) identify "three other genealogies: financial distress modelling, financial fraud modelling, and stock market prediction and quantitative modelling" (p. 102), which are part of the existing research on (big) data analytics. In particular, financial fraud modeling lies in proximity to parts of due diligence. It focuses on the detection of patterns and outliers, which also plays an important role in an FDD's quality of earnings analysis that seeks to detect potential normalizations. Similarly to auditing and FDD, the same auditing and advisory firms conduct fraud investigations.

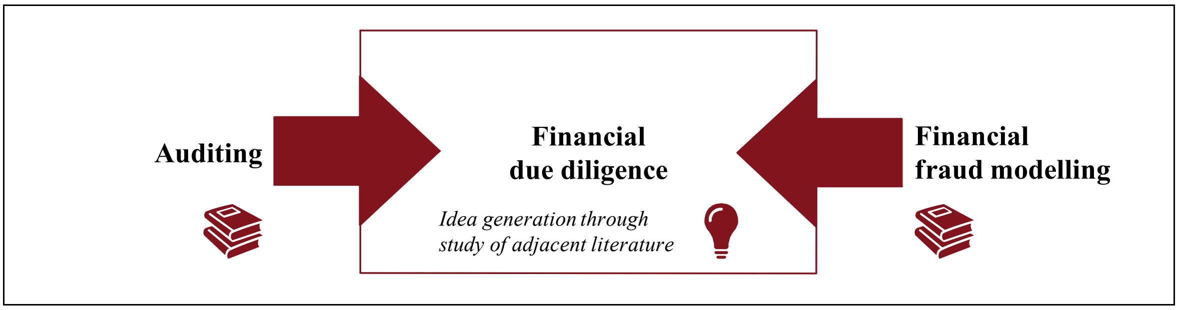
However, the process and content-related differences of these adjacent domains do not allow use cases to be transferred unmodified to FDD. Instead, the applications serve to develop initial ideas for potential use cases in FDD. Their practical application is tested during the expert interviews (see Chapter 5).

The above-described examination of adjacent literature streams is illustrated in Figure 3.9. Note that the vast majority of literature concerning the use of analytics stems from (external) auditing, while fewer studies address fraud detection (Appelbaum et al., 2018).[68] In addition, FDD has its largest intersections with the auditing discipline. Consequently, most studies from related literature examined in this thesis stem from the auditing field.

[67] For further differences between FDD and auditing, refer to Berens and Strauch (2011), Bredy and Strack (2011), Pomp (2015), and Tseng (2013).

[68] In the literature review concerning analytical procedure conducted by Appelbaum et al. (2018), 80% (241) of 301 prior studies address auditing, while only 14% (42) and 6% (18) of prior research concentrate on financial fraud detection and financial distress modeling, respectively.

Figure 3.9: Examination of adjacent research veins in the literature review



Source: Own illustration

The following sections provide a framework for the classification of different use cases in the literature veins described above as well as an overview of the current use of big data and data analytics techniques.

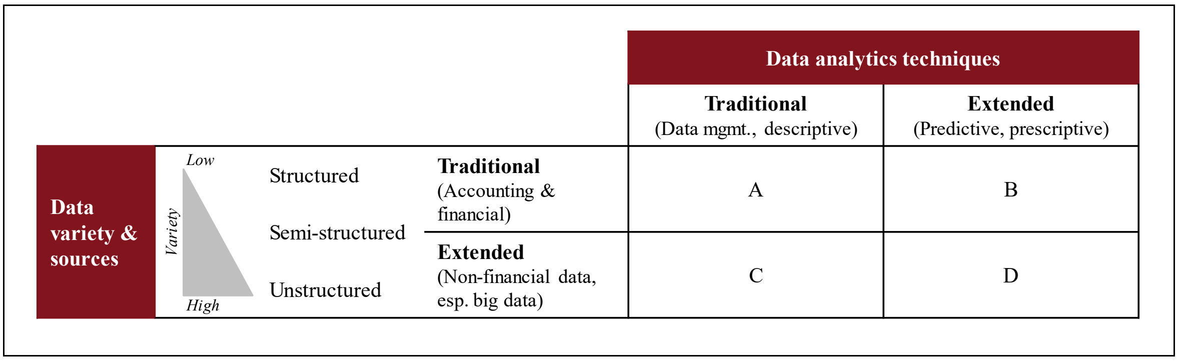
3.3.2 Classification of big data and data analytics applications

Alles and Gray (2016) have developed a model to classify the potential applications of different data sources and data analytics techniques that arise from the literature review in the above-mentioned research veins. They write that the concepts of big data and data analytics should be viewed in the lens of their interrelations, although they are often used independently (see Figure 3.10). To reflect the varying data structure across different sources, Ruhnke (2019) has added the element of data variety to Alles and Gray's (2016) conceptual framework.[69] The framework shows that the degree of analytical advancement can be determined by both the data sources used (as well as the respective data variety) and the data analytics methods applied.

The framework is reused to qualitatively assess the application of big data and analytics in FDD based on the findings of expert interviews (see Section 5.2.10).

[69] Moreover, Ruhnke (2019) enriches Alles and Gray's (2016) original framework with audit-specific analytics tools and techniques that are not included in Figure 3.10. Instead, the analytics tools and techniques employed in FDD are elaborated on in the further course of this dissertation (see Sections 5.2 and 6.6.4).

Figure 3.10: Classification of big data and data analytics applications



Source: Own illustration based on Alles and Gray (2016) and Ruhnke (2019)

While Section 3.3.3 deals with the continuum from traditional data to big data (vertical axis of Figure 3.10), Section 3.3.4 covers the different data analytics techniques of finance and accounting research (horizontal axis of Figure 3.10).

3.3.3 Use of big data sources

Alles (2015) and Salijeni et al. (2019) underscore the pressing demand from clients and other stakeholder groups for the increasing integration of big data into analysis rather than to continue relying on traditional data sources (e.g., finance and accounting modules of ERP systems). While the volume and velocity of data have increased sharply over time (towards full population data and real-time information) and are not fundamentally new to accountants, the largest difference between traditional data and big data lies in the variety of data (Arnaboldi et al., 2017; Bhimani and Willcocks, 2014; Borthick and Pennington, 2017; Janvrin and Weidenmier Watson, 2017; Lowe et al., 2017; Titera, 2013). The variety has escalated sharply, in particular with the increase of external web-generated data and sensor data (Janvrin and Weidenmier Watson, 2017; Warren, Moffitt, and Byrnes, 2015).[70] In contrast to traditional data, which is often collected for a specific purpose, big data contains large amounts of useless and unreliable information, i.e., it has a lower veracity (Arnaboldi et al., 2017; Constantiou and Kallinikos, 2015). Thus, the greatest challenge related to big data for accounting purposes lies in the more inductive identification of reliable and relevant information in the various big data sources (Arnaboldi et al., 2017; Yoon, Hoogduin, and Zhang, 2015).

[70] Warren et al. (2015) explain that approximately 90% of big data is of an unstructured nature.

Although the focus remains on traditional accounting data, there are multiple emerging sources of information that researchers have identified as potentially relevant to the finance and accounting domain – at least as supplemental evidence (Alles and Gray, 2016). For example, external audits often foresee an examination of the relationships between account balances and relevant non-financial information (Appelbaum et al., 2018; Louwers, Ramsay, Sinason, Strawser, and, Thibodeau, 2015). Academic recommendations for this non-financial big data range from realistic perceptions (e.g., sensor data) to ideas that lack practical relevance (e.g., client face recognition, which can lead to data privacy concerns).

3.3.3.1 Approach for the review of adjacent literature

The question necessarily arises regarding which of these big data examples and their related use cases possess practical relevance for FDD. For this reason, a structured literature review and analysis approach is applied (see Figure 3.11).

Figure 3.11: Approach for the review and analysis of adjacent literature

Source: Own illustration

After the initial identification of adjacent literature streams (see Section 3.3.1), a keyword and reference-based search leads to the most relevant studies for the field at hand. Subsequently, different big data sources are identified, split into internal and external data sources, and structured along eight categories: text document data, website and social media data, transactional data, sensor data, geolocational and geospatial data, audio data, image data, and video data (see Table 3.2).

Table 3.2: Classification of big data sources in finance and accounting research

Data variety	Data type	Origin of data	
Indicative scale		Internal examples	External examples
Medium (= semi-structured or unstructured)	**Transactional data**	• Internally generated data from transactions (e.g., financial, logistical)	• Externally generated data from transactions (e.g., financial, logistical)
	Sensor data	• Data from radio-frequency identification (RFID) tags, infrared, wireless local area network (WLAN) • Internet of things (IoT)/machinery data	• Weather data
	Geolocational/ geospatial data	• Global positioning system (GPS) locational data	• Satellite map data
	Text document data	• Company reports and press releases • Internal e-mails (e.g., to customer services) • Internal documents • Meeting minutes	• Market and industry reports • Competitors' reports and press releases
	Web and social media data	• Website traffic • Website user behavior	• Social media commentary data (product mentions, product-related customer conversations, posts about products) • Social media action data (likes, shares, retweets) • News and web log mentions • Electronic market data, sales lists, and infomediaries' price lists
	Audio/voice data	• Internal phone calls • Calls to customer services • Conference calls	• Podcast news • Competitors' conference calls
	Image data	• Surveillance imagery	• Company and product-related images uploaded by customers
High (= fully unstructured)	**Video data**	• Videos of PPE and machinery • Surveillance video footage	• Company and product-related videos uploaded by customers

Source: Own illustration

In the next step, the related use cases are clustered into six topics, which link the different usage options: revenue validation and forecasting, identification of cost opportunities, fixed asset validation, inventory validation, warranty liabilities validation, and fraud risk evaluation (see Table 3.3). Dividing the use options into these categories demonstrates that using big data can enhance the analysis of financial statements and income statements (Saggi and Jain, 2018). The following figure presents different use cases and is guided by those six overarching topics. Finally, the topics stemming from adjacent literature streams are assessed for their relevance to FDD.

Table 3.3: Big data-based use cases in finance and accounting research

Use case in finance & accounting	Data sources (examples)
Revenue validation and forecasting • Customer satisfaction • Product/service popularity • Level of competition • Bargaining power of buyers/suppliers • Macroeconomic trends and industry data • Seasonal effects	• Social media/news mentions • Company and product-related images and videos uploaded by customers • Customer feedback on websites and social media • Calls/e-mails to customer services (e.g., complaints and inquiries) • Website traffic (vs. competitors) • Video footage of stores • Company reports and press releases • Conference calls • Competitors' reports and press releases • Market and industry reports • Weather data
Identification of cost opportunities • Operations efficiency • Employee productivity	• IoT/machinery data • Videos of PPE, machinery, inventory • Workplace videos • Employee e-mails and phone calls
Fixed asset validation • Asset existence • Fair value estimation/validation • Impairment need	• Satellite map data • IoT/machinery data • Electronic market data, sales lists, and infomediaries' price lists • Videos of PPE, machinery, inventory
Inventory validation • Level inventory • Cost of inventory	• RFID transponder data • GPS locational data • Infrared and WLAN data • Electronic market data, sales lists, and infomediaries' price lists
Warranty liability validation • Warranty liability for product replacement	• Customer feedback on websites and social media • Calls/e-mails to customer services (e.g., complaints and inquiries) • Company and product-related images and videos uploaded by customers
Fraud risk evaluation • Fraud risk prediction	• Employee e-mails/calls (e.g., tone)

Source: Own illustration

3.3.3.2 Big data-based revenue validation and forecasting

Most big data-based use cases from finance and accounting are comprised of revenue validation and forecasting. The most frequently cited data sources concentrate on consumer data, particularly those data shared in the Internet. Additionally, internal and external data on competition, supply, market trends, and further price or sales-related variables are used to enhance revenue predictions.

Customer satisfaction

A central influence factor in the buyer decision process is customer satisfaction. The consumer's satisfaction, and ultimately its impact on the level of sales, can be modeled using various sources of big data (Yoon et al., 2015). For example, Warren et al. (2015) write that advanced analytics techniques can be employed to measure satisfaction levels based on "customer feedback on websites and social media (e.g., positive words and phrases), customer telephone complaints and inquiries (e.g., vocal stress and tension), and Internet video reviews posted by customers and bloggers (e.g., frowns and other negative gesturing)" (p. 400). Beyond social media, news, web logs, and message boards also play a role in capturing data. When this data is integrated in the analysis of financial information, it gives some indications of customer satisfaction (Dai and Vasarhelyi, 2016; Issa et al., 2016). Alles (2015) notes that accountants can focus on analyzing rather than collecting this data, which is done by specialized service providers who accumulate and subsequently sell social media data. Beyond indirect customer feedback, direct feedback, for instance, text data from e-mails to and audio data from phone calls with the customer service, can also contain information about customer satisfaction (Murthy and Geerts, 2017; Warren et al., 2015). Warren et al. (2015) also suggest using customers' video-recorded body language as a proxy for consumer satisfaction. Moreover, data on customer satisfaction can be linked to geographical and demographic data in order to predict revenues in different locations (e.g., countries, stores) (Cao et al., 2015).

Product/service popularity

Another field of revenue forecasting is product and service popularity, which is closely related to customer satisfaction, but is more focused on the product and service side. Various information relevant to assessing product popularity, and thereby product sales, is found on social media. Murthy and Geerts (2017) divide usable social media data into commentary data (e.g., product mentions, posts and tweets about products, images of products) and action data (e.g., Facebook likes and shares, Twitter retweets). Both categories reflect customer sentiment about a firm's products and services (Murthy and Geerts, 2017). Issa et al. (2016) and Richins, Stapleton, Stratopoulos, and Wong (2017) state that text content and meaning, beyond pure product name mentions and customer sentiment, also play a vital role in measuring product popularity. These popularity measurements provide an additional dimension of support to firms in granularly determining their sales when broken down by geographies, split along the product mix, or divided along demographic customer segments (Vasarhelyi et al., 2015; Warren et al., 2015). In the auditing domain, product popularity can be used to detect inconsistencies between a particular product's sales and its reputation on social networks (Yoon et al., 2015).

Level of competition

The level of competition, a major influence factor for revenue development, can be more accurately captured using text data (Richins et al., 2017). Product market competition cannot be unidimensionally proxied for by industry concentration as done in prior studies (Karuna, 2007). Instead, the former measures can be supplemented by an analysis of unstructured text data. For instance, Li, Lundholm, and Minnis (2013) assess the level of competition based on the frequency of references to competition or to specific competitors in 10-K reports. Moreover, Richins et al. (2017) recommend also analyzing competitors' MD&A sections. In addition to text data, a comparison between the client's and its competitors' website traffic data could deliver insights into both past and future sales development (Yoon et al., 2015).

Bargaining power of buyers/suppliers

Similarly to using textual evidence for competition analysis, prior literature points towards employing textual information from SEC filings to determine the influence of buyers and suppliers (Richins et al., 2017). For instance, past research uses Capital IQ's text mining capabilities to extract the number of buyers and suppliers from SEC forms. These figures serve to generate proxies for the bargaining power of buyers and suppliers (Hampton and Stratopoulos, 2015).

Macroeconomic trends and industry data

Big data for revenue predictions may concern macroeconomic trends and industry data (Earley, 2015). For instance, prior studies discuss census and macroeconomic data that can be incorporated into the revenue planning process (Murthy and Geerts, 2017; Warren et al., 2015).

Seasonal effects

Finally, a prior study uses weather data from open sources to predict sales (Yoon, 2016; Yoon et al., 2015). This sensor data can be easily employed into revenue forecasting since they are continuously generated, collected, and are readily accessible (Issa et al., 2016).

3.3.3.3 Big data-based identification of cost opportunities

Prior literature presents different big data sources that enable the identification of efficiency and productivity levers, and thereby cost opportunities.

Operations efficiency

Data generated by Industry 4.0 – the connection of cyber-physical systems, the IoT, cloud computing, and cognitive computing – provides accountants with new possibilities to monitor operations and product quality. This data allows accountants to discover opportunities to streamline companies' operations, which results in cost reductions (Dai and Vasarhelyi, 2016; Richins et al., 2017). Moreover, accountants may use videos of inventory as supplemental evidence to measure throughput and detect bottlenecks (Metaxas and Zhang, 2013; Warren et al., 2015).

Employee productivity

Prior literature indicates that big data could also help accountants to determine individual employees' productivity. For instance, workplace videos facilitate the tracking of worker productivity (Metaxas and Zhang, 2013; Warren et al., 2015). In addition, Warren et al. (2015) suggest that the tone of e-mail and phone conversations could be used as a proxy for employee morale and that the number of e-mails sent by managers could constitute an indicator for productivity.

3.3.3.4 Big data-based fixed asset validation

Based on the different sources of big data used, accountants can validate the existence and valuation of assets, derive impairment needs, and identify investment bottlenecks.

Asset existence

The existence of certain assets, especially factories, can be confirmed using geospatial data (Murthy and Geerts, 2017; Warren et al., 2015). For instance, the SEC used satellite imagery to uncover accounting fraud when it convicted a homebuilder who falsified sales of more than 100,000 homes to inflate revenues (Huerta and Jensen, 2017).

Fair value estimation/validation

Going beyond confirming the existence of assets, programmed software agents could confirm level 1 and level 2 fair value estimates with automatically retrieved information from external market sources (Murthy and Geerts, 2017; Warren et al., 2015).[71] Such sources include peer benchmarks, extractions of pricing history in peer markets, and values of items in electronic markets, sales lists, and infomediaries' price lists (Vasarhelyi et al., 2015).

Impairment need
Another recommendation is to detect the condition of assets or impairment issues using different data sources, such as video recordings that reveal the condition of PPE, machinery data (Metaxas and Zhang, 2013; Warren et al., 2015), or data of equipment usage (Issa et al., 2016). Indications of impairments such as obsolescence or physical damage, idleness, and worse economic performance than expected, which are outlined in IAS 36, could be inferred from the big data sources previously outlined. In addition, Warren et al. (2015) explain that "audio interviews with construction engineers during the construction phase of plant assets offer additional evidence of their value and estimated period of benefit [and] potential impairment issues" (p. 399).

3.3.3.5 Big data-based inventory validation

RFID technology, which automatically identifies and tracks tags attached to objects based on electromagnetic fields, allows for advancements in the identification of inventories. Additionally, external price information facilitates the valuation of finished and unfinished goods.

Level of inventory
Traditionally, accountants evaluate inventories based on the LIFO and (according to IFRS exclusively) FIFO methods. Both approaches follow the assumption of a certain consumption of goods that are purchased at different prices. Prior studies have presented the idea that measuring the current value of held inventory using data from RFID transponders (Vasarhelyi et al., 2015) would lead to a more precise and less assumption-based inventory valuation. RFID tags embedded into inventory or pallets carrying inventory record product movements and can automatically update WIP, finished goods inventory, and goods-in-transit records in systems (Borthick, 2012; Issa et al., 2016). Other technologies, such as infrared, wireless, and GPS, could serve

[71] The fair value hierarchy (levels 1 to 3) and the respective inputs are regulated in IFRS 13. Level 1 inputs are described as quoted prices in an active market. Level 2 inputs refer to directly or indirectly observable inputs other than quoted market prices (e.g., quoted prices for similar assets or liabilities in active or inactive markets). Level 3 inputs are unobservable inputs due to little, if any, market activity.

the same purpose as RFID (Murthy and Geerts, 2017). Moreover, inventory video data may allow for assessment of real-time quantity changes (Metaxas and Zhang, 2013; Warren et al., 2015).

Cost of inventory

The exact determination of inventory consumption can be combined with the values of items in electronic markets, on sales lists, or on infomediaries' price lists to determine the cost of inventories using the retail method according to IAS 2 (Vasarhelyi et al., 2015). In the auditing context, the more precise tracking of both the amount and the value of inventory could serve to confirm the respective balance sheet positions (Vasarhelyi et al., 2015).

3.3.3.6 Big data-based warranty liability validation

As outlined in Section 3.3.3.2, consumer-related big data can be leveraged by accountants to forecast revenues. Additionally, such data provides useful information about product usage tendencies and defects that need to be reflected in firms' warranty provisions.

Warranty liability for product replacement

In quality control monitoring, analyzing text or audio data from customer e-mails and phone calls can facilitate the identification of troublesome product or service features (Richins et al., 2017; Warren et al., 2015). Moreover, product usage tendencies or defects can be detected using sophisticated computer algorithms, which process and interpret static images (Warren et al., 2015). With the application of algorithms for object and scene recognition (Torralba, Fergus, and Freeman, 2008) and crowd-sourced training of object detectors (Vijayanarasimhan and Grauman, 2014), companies are able to determine the condition and use of their products found in images uploaded by customers (Warren et al., 2015). Similar insight on consumer behavior can be gained from sensors, such as RFID tags, that are embedded into products (Murthy and Geerts, 2017). Knowledge of product usage and defects, can, in turn, improve valuation of warranty provisions. Warren et al. (2015) emphasize that inferences regarding customer satisfaction and product quality provide information that can be leveraged for the valuation of warranty provisions according to IFRS 15 and IAS 37. For instance, the rate of customer complaints may be related to the number of warranty claims.

3.3.3.7 Big data-based fraud risk evaluation

Finally, prior literature describes how big data can be used to detect fraud.

Fraud risk prediction

Employee e-mails are the primary source used in identifying fraud (Richins et al., 2017; Warren et al., 2015). For example, text mining is applied to e-mail messages to identify discontented employees and to predict organizational fraud risk (Holton, 2009). Fraud triangle analytics is an advanced analytics-based fraud discovery method that strives to identify employees, based on e-mail texts, who possess the opportunity, pressure or incentive, and rationalization to commit fraud (Debreceny and Gray, 2011). In addition to e-mail, extracted information from conference calls can be used to gain useful information for potential financial misstatements, as demonstrated in prior research (Sun, Liu, and Vasarhelyi, 2016; Sun and Vasarhelyi, 2016). Finally, security videos, news videos, and social network data can serve as an alternative source for observing fraud (Vasarhelyi et al., 2015).

3.3.3.8 Discussion of the use of big data

Salijeni et al. (2019) recognize that most of the big data use cases, which strive "to establish quantifiable indicators of highly subjective categories […] adopted by the Big Four firms[, are] still premature" (p. 14). Yet, the different applications of big data presented in finance and accounting literature already provide an indication regarding how such data could be used in FDD. First, some use cases are dedicated to intangible assets omitted on the balance sheet (e.g., customer base, product quality, vendor base, company reputation). These assets' values are difficult determine objectively (Kieso, Weygandt, and Warfield 2013; Warren et al., 2015). Yet, the increase in the ratio of off-balance sheet to on-balance sheet items due to faster growth of intangible relative to physical assets, suggests that these assets have become increasingly important (Warren et al., 2015). Second, many use cases serve to provide additional, often more precise information, to more accurately determine the value of income, expenses, assets and liabilities (e.g., inventory valuation). These two observations demonstrate the increased relevance of big data to supplement financial information when measuring elements not (or not properly) captured by traditional accounting concepts. Similarly, big data could be leveraged in FDD and enable new insights into business performance, risks, and opportunities that reach beyond those gained from traditional finance and accounting data (Cockcroft and Russell, 2018).

Overall, the literature in the areas of auditing and fraud detection provides a sound overview of the various possible uses of big data in the financial and accounting context. The use of big data for off-balance-sheet items and for the refinement of P&L and balance sheet items indicate a clear direction for potential use cases that are transferable to FDD.

In Chapter 5, expert interviews with leading practitioners help to validate these initial concepts based on prior academic research for the prospect of data usage for FDD. Validating existing ideas is an essential step as the "[c]ompetitive advantage can be greatly improved by leveraging the *right* [emphasis added] data" (ISACA, 2013, cited in Alles, 2015, p. 443). As the quote demonstrates, data selection is a crucial part of the analysis of (big) data. Alles (2015) confirms that it "is not just [important] that the business can claim to be using [b]ig [d]ata, but that the right data [is] being analyzed by the firm in the *right way* [emphasis added]" (p. 443). Accordingly, the next section deals with the use of different analytics techniques.

3.3.4 Use of data analytics

The finance and accounting discipline "represents a special case for investigation, having been involved in the analysis of large amounts of data for many years" (Cockcroft and Russell, 2018, p. 324) and is still in its infancy regarding the application of analytics methods. The emergence of big data, coupled with increasing volumes of traditional, mostly structured data, makes long-established analysis tools inadequate and prompts the need for new tools and techniques to address issues of scalability, adaptability, and usability (Borthick and Pennington, 2017; Gepp et al., 2018; Saggi and Jain, 2018; Warren et al., 2015). Accordingly, the use analytics tools and techniques in due diligence and adjacent research streams is presented and evaluated in the following.

3.3.4.1 Data analytics in due diligence literature and practice

Prior research on the practical use of such novel tools and techniques in M&A, or more specifically FDD, is limited to a few contributions in practically oriented journals (e.g., Beckmann et al., 2019; Feix, 2018; Feix, 2019; Feix and Popp, 2018; Mackenstedt et al., 2018; Rauner, 2019). Therefore, this section initially lists the few publicly available use cases of data analytics tools in due diligence and subsequently concentrates on potentially transferable analytics use cases described in adjacent literature streams.

Examples of data analytics use cases stretch across all phases of the M&A process (Feix, 2019; Feix and Popp, 2018). In the transaction phase, financial, legal, and compliance due diligence are prime for the use of and partial automation through analytics (Feix, 2019; Feix and Popp, 2018). The most prominent use case in legal due diligence is machine learning-based contract analytics software that enables the semantic analysis of numerous contractual documents (e.g., representation and warranty clauses, exclusivity agreements, change-of-control clauses, and intellectual property rights) (Feix, 2019; Feix and Popp, 2018; Harder, 2020). Forensic analytics tools are used as part of the compliance due diligence (Feix, 2019). The use of analytics tools in FDD, apart from "automated [virtual] data room analysis" [translated from German] (Feix and Popp, 2018, p. 282; see also Matzen, 2018), is described in only two research articles. In his article on database-supported analysis tools in FDD, Rauner (2019) provides examples of the current practice. In particular, he distinguishes between analyses that are carried out entirely in data management software and those where the data, albeit prepared in this software, is analyzed in the traditionally used spreadsheet program Microsoft Excel. The first group comprises standard analyses in FDD (e.g., normalizations, transformation of the balance sheet into the net asset format) and analyses of large amounts of data (e.g., price-volume analysis on single product level). In contrast, the latter group includes analyses that are easier to perform outside the database (Rauner, 2019). For example, applications that particularly benefit from using data management software include the analysis of product portfolios by branch, credit portfolios, and customer portfolios. These applications also include sensitivity calculations of business plans and the development of financial information in carve-out transactions (Rauner, 2019). Beckmann et al. (2019) add further analyses that benefit from the examination of very granular data sets with analytics tools, such as revenue and profitability analysis, price-volume analysis, customer and product analysis, and analysis of seasonality effects. Overall, according to these two articles, analytics tools are primarily used in the analysis phase of the FDD process. This is particularly true when large amounts of very granular data are available, when analyses are highly standardized, and when analyses can benefits from the features of the tools such as filtering, slicing, and dicing according to multiple criteria (e.g., by customer, product, location).

As only the articles by Beckmann et al. (2019) and Rauner (2019) address the use of analytics in FDD, their findings are complemented by publicly available information from the Big Four companies. For instance, KPMG promotes its proprietary Strategic

Profitability Insights tool, which can produce detailed standardized reports from raw transaction-level data. The tool, which was developed with private equity firms as early adopters, focuses on revenue and margin analyses. These areas can be by quickly analyzed by customer, product, geography, and channel (KPMG Australia, 2018; KPMG U.S., 2019a). Moreover, KPMG demonstrates use cases for further proprietary machine learning and analytics tools, such as identifying growth and performance opportunities or estimating value potential within PE firms' portfolio companies (KPMG U.S., 2019b). Deloitte developed its offering in-house; iDeal is "a combination of tools, processes, and techniques" (Deloitte U.S., 2016a, p. 2) that was launched in 2016 in the U.S., Canada, the United Kingdom, Japan, and Australia. In due diligence, this solution focuses on analyzing micro-level details that could not be captured by traditional tools (Deloitte U.S., 2016b). EY uses the terms BI, smart data discovery, data science (EY U.S., 2020), and social media analytics (EY, 2016) to describe its application of analytics in due diligence services. The firm provides a case study with a focus on descriptive analytics and visualization tools such as TIBCO Spotfire, Tableau, or Power BI in the due diligence phase (EY U.S., n.d.). Another of their publications states that EY also uses predictive, and prescriptive in sell-side mandates (EY, 2017) – albeit without providing further evidence. Finally, PwC promotes its use of descriptive and predictive analytics in the pre-deal phase, primarily in the business valuation and scenario analysis (PwC U.S., 2018). The firm highlights its use of analytics tools such as "[v]isualization tools supported by a dynamic online platform" (PwC U.S., 2018, p. 2) in typical due diligence tasks, such as examining past performance to challenge assertions made by the seller on the business plan. In particular, PwC highlights its approach to develop a single source of truth or "common information platform" (PwC U.S., 2018, p. 4) for each client from the different sources of internal and external data gathered. The tools employed by PwC's Swiss organization include Alteryx Designer, Tableau, Microsoft Excel itself and its add-ins Power Query/Get & Transform and Power Pivot, Microsoft Power BI, and the planning software Anaplan (Westermann and Singh, 2018). Overall, the information made publicly available by the Big Four paints the picture of a descriptive and partly predictive use of a diverse set of a few proprietary and a broad range of off-the-shelf software tools. Although use cases vary, a focus area can already be deduced: past performance. The extent to which these initial findings from only a few, mainly American, sources can be transferred to the German-speaking realm remains to be determined.

Beckmann et al.'s (2019) and Rauner's (2019) findings, as well as the publicly available information from the Big Four firms, illustrate first examples for the use of data management and analytics in FDD. However, especially in the cases of Beckmann et al. (2019) and Rauner (2019), these examples are limited exclusively to target-internal, mainly financial information and therefore only cover part of the spectrum.

3.3.4.2 Data analytics in adjacent literature streams

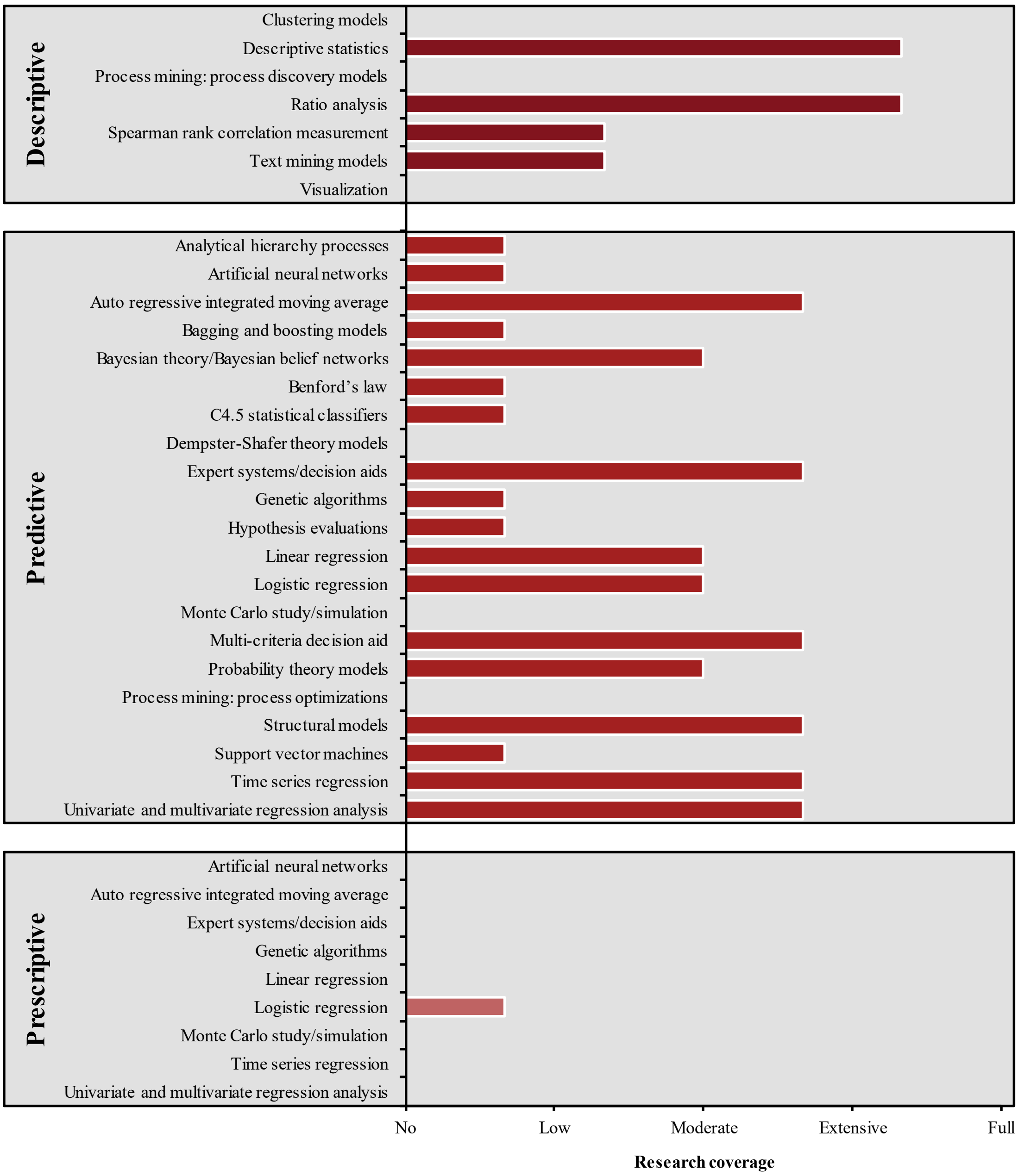
As the knowledge regarding data analytics tools and techniques in FDD is limited to two prior studies and publicly available information from the Big Four, henceforth adjacent literature is used. This approach is intended to identify use cases that may be transferred to FDD in modified form.

The use of different analytics procedures in the research vein closest to FDD, the external auditing area (see Section 3.3.1), is examined by Appelbaum et al. (2018) through the review of 301 papers. Their study highlights the gaps and areas of scant research for each orientation of analytics (descriptive, predictive, and prescriptive) and its respective techniques. Figure 3.12 presents a simplified summary of the overview from Appelbaum et al.'s (2018) study.[72] The overview quickly demonstrates that most research papers focus on descriptive and predictive analytics. The coverage of different techniques within these two data analytics orientations, however, varies greatly.[73] By contrast, past literature almost completely ignores the field of prescriptive analytics. Consequently, the following literature review concentrates on descriptive and predictive analytics exclusively.

[72] To simplify the table shown in the original study, the number of phases of the auditing process with sufficient literature coverage was counted and converted into a bar chart.

[73] For a few data analytics techniques, prior literature exists in adjacent research veins other than auditing. For instance, visualization is addressed in the financial fraud modeling discipline.

Figure 3.12: Research coverage of data analytics techniques



Source: Own illustration based on Appelbaum et al. (2018)

In their literature review, Appelbaum et al. (2018) highlight typical tasks of an audit assignment that provide opportunities for, or even necessitate, the use of data analytics. They include examples such as the comparisons of current accounts either between historical periods or to the budget, evaluations of the conformity of account balances with previously predicted patterns, comparisons of financial ratios with competitors, and examinations of the relationships of account balances with non-financial information (Louwers et al., 2015). These examples demonstrate that modern audit engagements do not rely purely on the analysis of historical financial data but also contain forecasts of future developments and embed non-financial data.

The concrete use of analytics techniques in the different phases of the external auditing engagement cycle[74] and corresponding considerations for FDD are described as follows.

In the (i) engagement step, auditors gain access to public information (e.g., previous financial statements) and external sources of data to obtain an understanding of the audited entity. With the help of ratio analysis, text mining, visualization, and descriptive statistics, they develop expectation models (Appelbaum et al., 2018; Stewart, 2015). In particular, ratio and financial statement analyses bear a high potential for automation (Richins et al., 2017). Analogously, the development of expectations (e.g., hypotheses concerning financial risks or value drivers to support the equity story) in the preparation phase of FDD could rely on similar model building techniques.

The subsequent (ii) planning and risk assessment provides initial access to the recent unaudited financial statements. The auditors rely primarily on ratio and trend analysis – supplemented by clustering, visualization, regression, belief networks, expert systems, and descriptive statistics – to refine their previously established models (Appelbaum et al., 2018; Stewart, 2015; Yoon, 2016). Data mining is employed to recognize patterns in the data (e.g., anomalies, discrepancies) that indicate accounting risks (Amani and Fadlalla, 2017). Similarly, data mining and visualization techniques are used not only in the auditing discipline but also in fraud investigations to detect suspicious transactions or employee behavior (Dilla and Raschke, 2015; Gray and Debreceny, 2014). In this context, Dilla and Raschke (2015) emphasize the need for interactive visualization tools, as they consider the graphical analysis with spreadsheet programs to be "cumbersome – if the user wants to change the variables being graphed or focus on a subset of the data, it is usually necessary to generate a new graph" (p. 2). In contrast, interactive data visualization presents results "via an easy-to-use interface often used as a component of data analytics" (Janvrin, Raschke, and Dilla, 2014, p. 31). Perkhofer, Hofer, Walchshofer, Plank, and Jetter (2019) present

[74] The division of the audit engagement cycle into different phases is based on Appelbaum et al. (2018).

two ways for how analytics tools enhance visualization. On the one hand, conventional forms of visualization used for structured data (called type I) can be used in an interactive form (e.g., by fast aggregation, filtering, or drill-down of the data). On the other hand, new forms of visualization (called type II) are particularly suited to identifying relationships, outliers, and patterns in large, unstructured data sets. Similar to the risk assessment in an audit or fraud detection, FDD consultants could leverage analytics techniques such as clustering and (interactive) visualization to identify previously unknown data patterns, such as anomalies in the quality of earnings analysis. They could also use the aforementioned techniques to recognize and verify trends and develop an independent, forward-looking perspective in order to validate the business plan as part of FDD.

The (iii) substantive testing and compliance testing and (iv) review phases of an external audit use benchmarking and previously developed expectation models to validate transactions and identify exceptions, which are flagged or require conducting further tests. Various analytics techniques can be applied in these phases including clustering, text mining, process mining, visualization, support vector machines, artificial neural networks, expert systems, decision trees, probability models, belief networks, genetic algorithms, multi-criteria decision aids, regression, Benford’s Law, descriptive statistics, structural models, and hypothesis evaluation (Appelbaum et al., 2018; Dechow, Ge, Larson, and Sloan, 2011). For key analyses, audit professionals often rely on CAATs, a “computer software that allows auditors to perform data analytics” (Chan and Kogan, 2016, p. 121). Chan and Kogan (2016) highlight the advantages of CAATs: testing large data sets (e.g., entire populations) instead of only small samples as well as achieving performance benefits through (partial) automation. Similarly, FDD’s core phase, the analysis, could benefit from analytics that would allow for greater depth in the different profitability, balance sheet, and cash flow analyses and would also allow for an increasing degree of automation in standard analyses. In particular, exceptional cases and outliers could be more easily identified and could even be (partially) automated as part of a quality of earnings analysis. However, most FDD analyses are likely to be mainly descriptive in nature – as are audit examination techniques (e.g., basic transaction tests, three-way matching, ratio analysis, sampling), which are the key tests in external audits (Appelbaum et al., 2018).

According to Appelbaum et al. (2018), prescriptive analytics that build on approaches from earlier phases are expected to improve the quality and transparency of the (v) audit opinion and reporting. Thus, Appelbaum et al. (2018) anticipate a stronger prospective use of time-series regression, probability models, belief networks, expert systems, and Monte Carlo simulation studies; however, this is still subject to further research. For instance, Chan and Kogan (2016) lay out a revenue prediction based on a time-series regression model. FDD service providers could also use advanced analytics techniques to design a more forward-looking validation of the business plan that builds on prior analyses of the historical situation.

In summary, with regard to analytics techniques, existing literature clearly focuses on descriptive and predictive techniques, while prescriptive analytics does not yet play a significant role. Previous analytics applications put forth in adjacent literature streams reveal four topics that could be of importance for FDD: (i) the development of business driver hypotheses in the preparation phase, which are validated with additional data during the subsequent analysis phase, (ii) the automated conduct of standard analyses, (iii) the identification of anomalies and outliers (e.g., as part of the quality of earnings analysis), and (iv) the creation of an alternative business plan.

3.3.4.3 Discussion of the use of data analytics

In light of increasingly large and unstructured data sets, the literature in both the M&A field and in the areas of auditing and fraud detection underline the need for using analytics techniques and technologies. The focus in both areas is primarily on descriptive analytics. Predictive analytics has hitherto only been dealt with outside the due diligence literature; prescriptive analytics is not relevant in either area.

The two relevant articles on FDD, as well as public information provided by the Big Four auditing companies, primarily present the use of data analytics tools and techniques in the analysis phase of FDD. In this phase, analytics tools are mainly used to benefit from advanced features (compared to traditional tools), to carry out standard analyses (e.g., normalizations), and when very large amounts of data are available. Examples for the latter case are principally drawn from profitability analysis (e.g., price-volume analysis, customer and product analysis), one of the four core areas in the analysis phase (see Section 2.2.4.4). Possible applications in the preparatory and reporting phases are not discussed. Furthermore, the two articles concentrate exclusively on the use of internal data obtained from the target company.

Adjacent literature is reviewed to generate further ideas for possible analytics applications. These ideas are outlined here. First, the use of analytics is not limited to the analysis phase. In external audits, different analytics techniques are used to derive expectations and build initial hypotheses in the early phase of the engagement. Analogously, analytics could enhance the early identification of the most relevant areas of risks and value potentials for a subsequent in-depth analysis. This practice could be of particular relevance for FDD and make it possible to prioritize which focus areas to subject to a later review, thus alleviating time pressure. However, the typically substantially shorter lead time before the start of an FDD project (compared to a regular audit) could be an impediment. Second, the (partly) automated performance of standard analyses, which is already carried out in the auditing domain, is in line with existing due diligence literature. In both disciplines, auditing and FDD, descriptive analyses have become increasingly automated. However, the higher level of formal requirements results in a more structured review process, which facilitates the automation of audits as compared to FDD. Third, the identification of anomalies and outliers through data mining and visualization techniques could be transferred to FDD, e.g. to enhance the quality of earnings analysis. However, the detection of anomalies is a regulatory activity in the audit, whereas in FDD it is only relevant in certain instances. Finally, predictive analytics techniques could be employed to verify management assumptions concerning the prospective development of the target. Predictive analytics could even be employed to create an independent, alternative business plan. To summarize, the adjacent literature expands the scope of the currently reported use cases beyond the exclusive use of descriptive analytics in the analysis phase. However, actual practices might differ from these theoretical considerations.

3.4 Summary

The introduction of BI and the subsequent evolution of technology-based analytics solutions began in the mid-20th century. While research has concentrated on the data management components of BI systems for decades, the focus is increasingly shifting to the analytics component. In particular, big data, which is characterized by its volume, variety, and velocity, has fueled the rise of advanced analytics to infer data veracity and value. Advanced analytics encompass both predictive and prescriptive orientations. Unlike more established descriptive analytics, these two forms take a forward-looking perspective.

Accordingly, the topics of (i) big data and (ii) data analytics have gained in importance in finance and accounting research. However, this applies to neither M&A in general, nor due diligence in particular. The scant research in the due diligence field requires reviewing literature from the adjacent domains of auditing and fraud modeling.

For eight different categories of (i) big data, related use cases can be clustered in six overarching themes: revenue validation and forecasting, identification of cost opportunities, fixed asset validation, inventory validation, warranty liabilities validation, and fraud risk evaluation. A large spectrum of big data sources is employed across the various use cases – with no clearly discernible focus. Nevertheless, two overarching objectives of using big data sources can be identified: Big data is utilized to obtain indications for the valuation of off-balance-sheet items, which are difficult to measure with traditional methods, and it is used to supplement financial information in order to more accurately determine P&L and balance sheet items. To conclude, the integration of big data sources into FDD – similarly to other disciplines of finance and accounting – could both broaden the spectrum of analyses and increase their level of detail and accuracy.

With regard to (ii) analytics techniques, existing literature focuses on descriptive and, in external auditing and fraud detection, also on predictive techniques. Prescriptive analytics do not yet play a significant role in either due diligence-related studies or adjacent studies. The only two articles by Beckmann et al. (2019) and Rauner (2019) that address the application of data analytics tools and techniques in FDD mainly concentrate on standard analyses and in-depth profitability analyses based on large, very granular data sets. In contrast, literature in both the auditing and fraud identification domains demonstrate that applications of analytics are neither limited to a purely descriptive orientation nor only to the analysis phase. Consequently, one of the four use cases that could be transferred to FDD builds on predictive analytics (development of an alternative business plan), while another one already takes place in the preparatory phase (derivation of initial risk and value-related hypotheses and expectations). The other two proposed applications (automation of core analyses and identification of anomalies in the quality of earnings analysis) are closer to the existing use cases described by Beckmann et al. (2019) and Rauner (2019).

This thesis contributes to research by demonstrating how potentially transferable use cases can be developed from adjacent literature streams. At a later stage, expert interviews with leading practitioners make it possible to validate these scientific recommendations for prospective big data and data analytics usage in FDD (see Chapter 5). The generalizability of the findings is then tested (see Chapter 6).

4 Technology adoption – Theoretical background and application

This chapter compares different adoption theories, presents the two models of choice, and depicts relevant empirical findings on technology adoption in the finance and accounting literature. The first section presents the spectrum of research approaches in the field of technology adoption. It then provides an overview of the most prominent adoption theories both on the organizational and on the individual level. Importantly, most prior literature has concentrated on a few theories and has not achieved a critical review across such a large spectrum with 16 different adoption models and extensions. After the model assessment, two theories that will be applied in this thesis are highlighted: the Technology-Organization-Environment (TOE) framework (organizational level) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (individual level) (Section 4.1). In a subsequent literature review, audit firms' adoption of technology in general, and data analytics solutions in specific, is scrutinized. The vast majority of earlier research follows a qualitative approach and is not guided by a selected theoretical adoption model. Hence, this dissertation strives to go beyond identifying the various influencing factors. It also connects them to the main constructs of the TOE framework and UTAUT (Section 4.2). The chapter closes with a brief summary (Section 4.3). It is important to note that this dissertation, in contrast to the majority of previous research, considers both levels of adoption, organizational and individual, to provide a comprehensive overview of the adoption of analytics in FDD.

4.1 Technology adoption theory

As a prerequisite for technologies to improve existing processes, they must be accepted and used by employees in organizations (Oliveira and Martins, 2008; Venkatesh, Morris, Davis, and Davis, 2003). Hence, it is essential to understand the determinants of adoption (Oliveira and Martins, 2008). Here, technology adoption theories support academic research in examining the critical use and adoption of technological innovation, providing explanations for adoption and non-adoption, and deriving recommendations of action for practice.

The investigation of the use, adoption, and spread of technologies can follow three approaches: the domestication approach, the diffusion approach, and the adoption approach (Pedersen, 2005).

The domestication approach concentrates on the societal consequences of the use of technological innovation and its integration into everyday life (Pedersen, 2005). Since domestication research takes a sociological perspective, which differs widely from the other two approaches, this thesis does not go into more detail on this approach.

Diffusion research examines the aggregate adoption process of innovations (Pedersen, 2005). The typical S-shaped function describes adoption over time from an a posteriori perspective and allows for the classification of users into different types of adopters (Mahajan, Muller, and Bass, 1990; Rogers, 2003). To describe the pattern of innovation diffusion and to predict future adoption, related studies consider explanatory factors such as interpersonal influence, sociodemographic factors, marketing activities, and other communication channels related to innovation (Rogers, 2003). It becomes evident that the drivers and inhibitors of organizational or individual adoption decisions cannot be identified on the basis of a social system's cumulative adoption decisions. Moreover, insufficient explanation for different diffusion patterns does not allow for deriving recommendations for improving the observed adoption process (Litfin, 2000). The diffusion approach, therefore, appears unsuitable to contribute to answering the research questions examined in this dissertation.

Adoption research, in contrast, uses cognitive approaches and psychological theories to explain the decision-making process of an organization or individual when choosing to use a new technology (Pedersen, 2005). Adoption research mainly differs from diffusion theory in its perspective of time and in the level of aggregation. In contrast to diffusion theories, adoption studies can also take an a priori view. Moreover, the object under investigation is seen on a single level rather than on an aggregated level. Since this thesis strives to explore the different influencing factors on both the organizational and individual adoption levels, it focuses on the adoption approach.

In the following sections, adoption theory in general (Section 4.1.1), and the prevalent adoption models in particular, are introduced. This culminates in the choice of two models for the analyses in this dissertation (Sections 4.1.2 and 4.1.3).

4.1.1 Introduction to adoption theories

In general, adoption models can be distinguished between their focus on technology decisions on either the organizational and firm level (see Section 4.1.2) or the individual level (see Section 4.1.3), respectively (Frambach and Schillewaert, 2002; Oliveira and Martins, 2008). Jeyaraj, Rottman, and Lacity (2006) circumscribe the distinction between both levels based on the different focus units.

As illustrated in Figure 4.1, both the firms' and the employees' intentions and decisions are intertwined.[75] While the organizational level reflects the management's decisions and subsequent efforts to introduce a new technology, this does not guarantee successful adoption as user acceptance may not transpire. On the other hand, a strong intention by individual co-workers to integrate IT in their work may still be insufficient for a successful adoption because such tools are not sufficiently provided by the firms' management. For that reason, this thesis will examine adoption on both the individual and firm level to allow for comparisons between and within organizations.

Initially, the organization creates awareness about the technological innovation and develops an attitude towards the innovation. It then evaluates the innovation and finally decides whether to invest into the innovation and make use of it (Frambach and Schillewaert, 2002; Hameed, Counsell, and Swift, 2012). However, it must be noted that "this organizational adoption decision is only the beginning of implementation" (Frambach and Schillewaert, 2002, p. 164). The successful adoption of a new technology in an organization also requires acceptance and use within the organization, i.e., at the individual level (Frambach and Schillewaert, 2002; Hameed et al., 2012).[76] Once an organization has decided to adopt a new technology, it may follow three fundamentally different strategies to facilitate adoption at the individual level. First, the management can mandate that the employees adopt the innovation (total commitment implementation strategy). Second, the management can facilitate adoption by providing the required infrastructure and support for users, while the actual usage remains voluntary (support strategy). Third, it can prolong the decision regarding full

[75] Frambach and Schillewaert (2002) note that adoption in an organizational context depends on both the organizational adoption decisions and the adoption by individuals within an organization. In contrast, "in consumer markets, the individual is the primary unit of analysis" (p. 163).

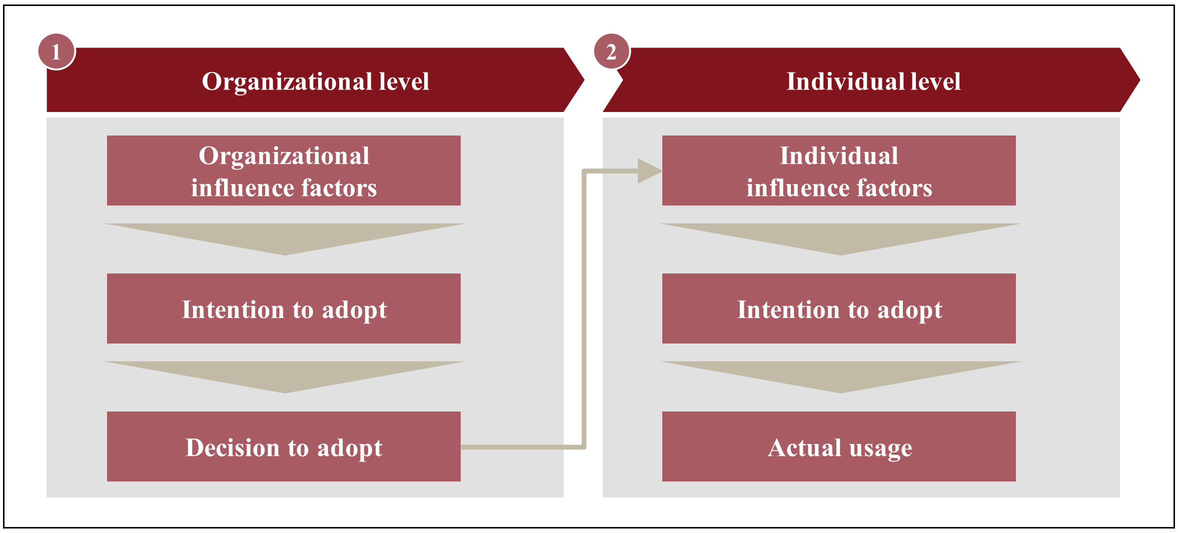
[76] Frambach and Schillewaert (2002) refer to this condition as "intra-organizational acceptance" (p. 164). In contrast, they describe the individual reliance on a prior organization adoption decision as "contingent innovation decision" (p. 164).

implementation based on insights from specific pilot projects within the firm (advocacy strategy) (Gallivan, 2001).

This simplified concatenation of adoption requirements embodies the sequential dependencies between organizational (first stage) and individual (second stage) decisions (see Figure 4.1). This sequence is often labeled as two-step adoption (Leonard-Barton and Deschamps, 1988) or two-stage implementation (Lucas, Ginzberg, and Schultz, 1990). Zaltman, Duncan, and Holbeck (1973) describe the initial firm-level decision to adopt an innovation as primary adoption and the actual implementation, which includes individual adoption by users, as secondary adoption (Gallivan, 2001; Zaltman et al., 1973).

Building on this argumentation, the majority of individual adoption research uses either behavioral intention or actual use to measure adoption. In contrast, organizational adoption studies often define adoption as decision to adopt or intention to adopt (Jeyaraj et al., 2006). The differences in measurement underline the need to consider organizational and individual adoption as a two-step process, where actual use requires a prior decision in favor of introducing a new technology.

Figure 4.1: Two-stage view of technology adoption decisions



Source: Own illustration

To the best of the author's knowledge there is no empirically validated and widely accepted model that unifies the organizational and individual levels of technology adoption. Significantly, Jeyaraj et al. (2006) stress "the lack of integration and understanding of the linkages between individual and organizational adoption of IT innovations" (p. 2). The difficulty of interlinking both perspectives lies in the fact that the information provided by different companies on their adoption decisions (subject of analysis: organizations) must be linked with the answers given by their employees (subject of analysis: individuals). This is difficult to portray for various reasons (e.g., guarantee of anonymity for the respondents).

Previous research has therefore sought to reflect organizational decision factors in studies that focus on individual adoption. Kimberly and Evanisko (1981) made first attempts at combining different perspectives. Their study highlights a model that contains individual, organizational, and contextual factors, though the individual variables aim to capture the characteristics of organizational leaders (i.e., tenure, cosmopolitanism, educational level, and involvement) rather than those of the employees expected to adopt. Similarly, Iacovou, Benbasat, and Dexter (1995) examine organizational readiness, external pressure, and perceived benefits to explain IT adoption. Again, the factor of perceived benefits relates solely to the managerial perspective and does not account for the perceptions of prospective users. In their literature review of firm-level adoption models, Oliveira and Martins (2008) describe how different organizational adoption models have been combined. Among the studies they scrutinized, none develops a model that includes both the organizational and individual adoption view. Instead, previous adoption studies always maintain an either one or the other perspective. Even Roger's (2003) Innovation Diffusion Theory (IDT), which is the only theory that reflects both levels, is used to focus on either organizational or individual decision-making units without a sufficient explanation of their interrelations (Jeyaraj et al., 2006; Oliveira and Martins, 2008).

Frambach and Schillewaert (2002) take on the missing link between the two levels and develop a two-stage model, which first looks at the organizational level and then looks at the individual level. However, it represents a link between an organizational level model and an individual level model rather than a combined framework. Their model remains purely conceptual and, to the best of the author's knowledge, has not yet been empirically validated. Finally, it has a general, i.e., non-IT-specific, innovation focus. In sum, their contribution has to be understood as explaining the link between both levels rather than combining them.

In a later study, Jeyaraj et al. (2006) propose possible linkages between both levels. In particular, top management support, as well as different innovation characteristics and organizational characteristics, represent such connections between both levels. They suggest the inclusion of individual characteristics (e.g., computer experience, education, and user satisfaction) in organizational adoption studies, since prior research "rarely examine[s] how an organizational decision to adopt an innovation is actually implemented by individuals within the organization nor are the characteristics of those individuals studied" (Jeyaraj et al., 2006, p. 13). Finally, they propose the inclusion of environmental characteristics (e.g., external pressure and influence) in individual adoption research (Jeyaraj et al., 2006).

To some extent, the suggestions made by Jeyaraj et al. (2006) are heard in the scientific community. However, there is still no integrated model that has been empirically tested across different settings and that has gained wide use. The following examples demonstrate the state of research as outlined. For instance, Rosli, Yeow, and Siew (2012) present a purely conceptual, but not yet sufficiently operationalized approach to combining adoption at the organizational and individual level in the auditing domain. They propose enriching the TOE framework (see Sections 4.1.2.1 and 4.1.2.2) with considerations from the individual level based on the UTAUT (see Sections 4.1.3.1 and 4.1.3.2). However, the connections of determinants within the proposed model is neither theoretically backed nor empirically tested. Gangwar, Date, and Ramaswamy (2015) also seize the suggestions made by Jeyaraj et al. (2006) when developing and testing a model that combines an individual adoption theory, the Technology Acceptance Model (TAM) (see Section 4.1.3.1), with an organizational adoption theory, the TOE framework. However, the selection of variables has been tailored to the specific context (cloud computing). In addition, the model has not been further validated by other researchers outside the cloud computing field. The lack of empirical support, combined with the fact that the models outlined, as well as other integrated models, were not published in leading academic journals, indicates that the attempts to establish an integrated model are immature.

Overall, the sparse conceptual considerations and the missing empirical validation of an integrated model indicate that future studies must seize the initial cogitations already identified and advance integrated adoption research. Due to the lack of a sound theoretical and empirical basis for an integrated model, this thesis relies on separate empirical tests for the firm and individual level.[77]

Furthermore, for the investigation of organizational adoption factors, the organizational perspective can only be examined qualitatively (see Section 1.3). The population of FDD service providers (see Section 2.2.3.4) is too small to draw statistically robust conclusions from quantitative research models. Therefore, the organizational perspective is considered exclusively in the qualitative research section, whereas adoption at the individual level is examined in both the qualitative research section and the quantitative, survey-based research.

To conduct these empirical tests, the relevant models need to be identified. Table 4.1 provides an overview of the most prominent adoption theories and the extensions of those theories from the IS, psychology, and sociology disciplines. A graphical illustration of the relationships of the core constructs of each theory can be found in the appendix (see Figure A.1 to Figure A.15).

Table 4.1: Overview of technology adoption theories

Theory/model	Level	Core constructs	Primary contributions
Theory of Reasoned Action (TRA)	Individual	• Attitude towards the behavior • Subjective norm	Ajzen and Fishbein (1973, 1980); Fishbein and Ajzen (1975)
Theory of Planned Behavior (TPB)	Individual	• Attitude towards the behavior • Subjective norm • Perceived behavioral control	Ajzen (1985, 1991)
Theory of Interpersonal Behavior (TIB)	Individual	• Attitude towards the behavior • Social factors • Affective factors • Habit • Facilitating conditions	Triandis (1977, 1980)
Technology Acceptance Model (TAM)	Individual	• Perceived usefulness • Perceived ease of use	Davis (1986, 1989); Davis, Bagozzi, and Warshaw (1989); Venkatesh and Davis (1996)
Technology Acceptance Model 2 (TAM2)	Individual	• Perceived usefulness • Perceived ease of use • Subjective norm	Venkatesh and Davis (2000)
Technology Acceptance Model 3 (TAM3)	Individual	• Perceived usefulness • Perceived ease of use • Subjective norm	Venkatesh and Bala (2008)
Decomposed Theory of Planned Behavior (DTPB)	Individual	• Attitude towards the behavior • Subjective norm • Perceived behavioral control	Taylor and Todd (1995b)

[77] It must be noted that when separate analyses of an organizational adoption model and an individual adoption model are conducted, no links between the two levels can be studied.

Combined Technology Acceptance Model and Theory of Planned Behavior (C-TAM-TPB)	Individual	• Attitude towards the behavior • Subjective norm • Perceived behavioral control • Perceived usefulness	Taylor and Todd (1995a)
Model of Personal Computer Utilization (MPCU)	Individual	• Job-fit • Complexity • Long-term consequences • Affect towards use • Social factors • Facilitating conditions	Thompson, Higgins, and Howell (1991)
Social Cognitive Theory (SCT)	Individual	• Personal factors • Environmental factors • Behavior	Bandura (1977, 1978, 1982, 1986); Compeau and Higgins (1995)
Motivational Model (MM)	Individual	• Extrinsic motivation • Intrinsic motivation	Davis, Bagozzi, and Warshaw (1992), Igbaria, Parasuraman, and Baroudi (1996)
Task-Technology Fit Theory (TTF)	Individual	• Task characteristics • Technology characteristics	Goodhue and Thompson (1995)
Unified Theory of Acceptance and Use of Technology (UTAUT)	Individual	• Performance expectancy • Effort expectancy • Social influence • Facilitating conditions	Venkatesh et al. (2003)
Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)	Individual	• Performance expectancy • Effort expectancy • Social influence • Facilitating conditions • Hedonic motivation • Price value • Habit	Venkatesh, Thong, and Xu (2012)
Innovation Diffusion Theory (IDT)	Individual and organizational	• Relative advantage • Compatibility • Complexity • Trialiability • Observability	Rogers (1962, 1971, 1983, 1995, 2003)
Technology-Organization-Environment (TOE) framework	Organizational	• Technology • Organization • External task environment	DePietro, Wiarda, and Fleischer (1990)

Source: Own illustration

The selection of an organizational and an individual adoption theory for the purpose of this dissertation is discussed in the following sections.

4.1.2 Adoption at the organizational level

The basis of company-wide adoption is a firm's decision to introduce a new technology. Thus, this section is dedicated to adoption at the organizational level. Yet, contrary to the availability of literature on individual adoption, literature in this area is scarce (Yu and Tao, 2009).

4.1.2.1 Discussion of organizational adoption theories

In this section, the only two prominent organizational adoption theories from Table 4.1 (IDT and TOE) are critically evaluated with regard to their application in this dissertation. The descriptions refer to the original models and do not contain the minor adjustments made by subsequent studies.

After comparing both models and taking into account their major critiques (see Table 4.2), the TOE framework represents the model of choice for investigating an organization's adoption and use of data analytics in FDD for four reasons. First, the TOE framework is specifically tailored to investigating technology adoption, whereas the IDT was synthesized from hundreds of prior studies on a range of innovations and thus lacks a clear focus on technology (Chau and Tam, 1997; Gallivan, 2001). Second, the TOE framework can be applied in both mandatory and voluntary settings, whereas large parts of IDT were developed in the context of voluntary acceptance. Third, the TOE model, in contrast to IDT, takes into consideration multiple environmental factors such as competition, which could work as a barrier or a motivation to technology adoption (Lippert and Govindarajulu, 2006; Oliveira and Martins, 2008), in particular in the fiercely competitive market for due diligence services. Fourth, the flaws of the TOE model can actually be strengths. The flaws are that not testing new constructs has limited further development of the original model and that scant theoretical synthesis has taken place (Baker, 2012). The adaptability of the model's three core constructs across various studies coming from different technological, industrial, geographical, and cultural contexts through adjustments in measurement underline their applicability and the model's stability since the time of the initial development. The stability mainly traces back to the model's versatile character and the strong alignment with existing theories (e.g., IDT[78]) (Baker, 2012). Consequently, the model provides a comprehensive framework with sufficient flexibility for context-specific adjustments (e.g., adding the client perspective to the environmental context when dealing with professional services firms) (Baker, 2012). These aspects are particularly suitable for the qualitative research approach applied to the analysis of organizational adoption.

[78] The constructs of IDT overlap with the three contextual elements of the TOE framework as follows: individual leader characteristics and internal characteristics of organizational structure are comparable to the organizational context, external characteristics of the organization correspond to the environmental context, and Rogers' (2003) "implicit emphasis on technological characteristics of the innovation" (Baker, 2012, p. 12) is comparable to the technological context (Baker, 2012; Zhu et al., 2003).

Table 4.2: Critique of organizational technology adoption theories

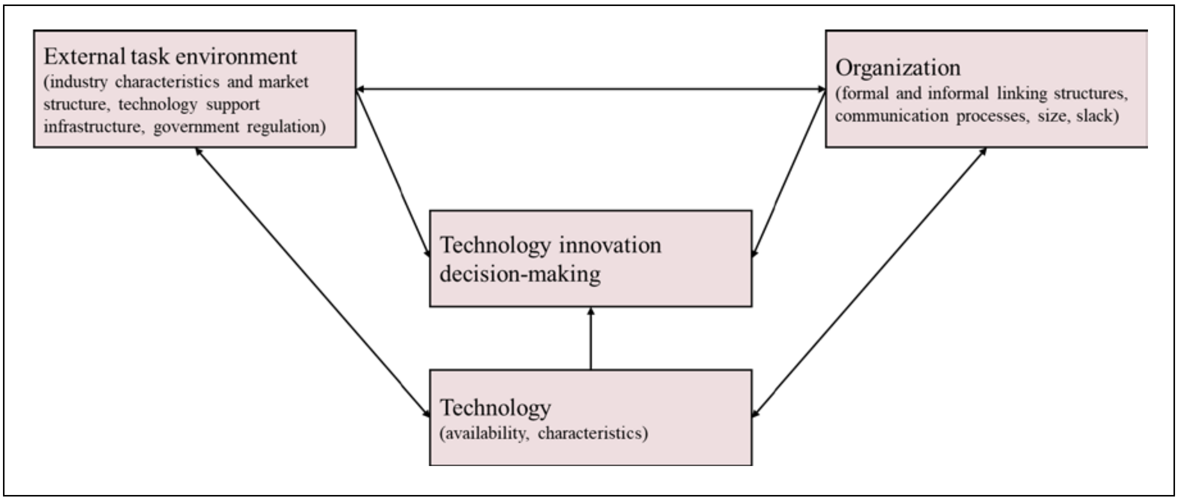
Theory/model	Main critique
Innovation Diffusion Theory (IDT)	• When the IDT is used at the organizational level, it **does not take into consideration the environmental factors** where the organization conducts business, such as competition, which could work as a barrier or a motivator to technology acceptance and adoption (Lippert and Govindarajulu, 2006; Oliveira and Martins, 2008). • The strong abstraction with the **dichotomy between adoption and rejection** of an innovation systematically **prevents the granular analysis** of different levels of IT use and of important context factors in the individual takeover process (Bayer and Melone, 1989; Karnowski and Kümpel, 2016). • The model **lacks specificity**, since it was developed to examine the diffusion of any type of innovation (Chau and Tam, 1997; Gallivan, 2001). • **Not necessarily all stages** of the decision-making process proposed by IDT **are passed** for an innovation (Lyytinen and Damsgaard, 2001). • Large parts of IDT were developed in the **context of voluntary acceptance** or rejection of an innovation based on the expected benefits and do not sufficiently consider settings in which IT adoption is encouraged by management (Leonard-Barton and Deschamps, 1988) or is compulsory (Moore and Benbasat, 1991).
Technology-Organization-Environment (TOE) framework	• Large parts of the theoretical development, with respect to the TOE framework, are confined to identifying the various critical factors in different adoption contexts. This has led to a **neglect of possible new constructs**, which could enrich the framework (Baker, 2012). • **Little theoretical synthesis** has occurred and critique offered has been scant (Baker, 2012).

Source: Own illustration

The TOE framework developed by DePietro et al. (1990) explains that three different elements of a firm's context influence adoption decisions: the technological, organizational, and environmental contexts.[79] These elements present "both constraints and opportunities for technological innovation" (DePietro et al., 1990, p. 154). Thus, they influence the way a firm sees the need for, searches for, and adopts new technology. The technological context includes the relevant technologies' availability and their characteristics. The organizational dimension refers to the firm's characteristics and resources, including linking structures between employees, intra-firm communication processes, firm size, and the amount of slack resources. Finally, the environmental context encompasses industry characteristics and market structure, technology support infrastructure, and the regulatory environment (Baker, 2012).

[79] It should be noted that the development of the TOE frameworks is ascribed to DePietro et al. (1990) and not – as often incorrectly cited – Tornatzky and Fleischer (1990). The originating authors' work is a chapter in a book edited by Tornatzky and Fleischer (1990).

Figure 4.2: Technology-Organization-Environment framework



Source: Own illustration based on DePietro et al. (1990)

4.1.2.2 Technology-Organization-Environment framework

Following the introduction to the TOE framework in Section 4.1.2.1, this subchapter describes its key constructs (technology, organization, external task environment) in more detail. For each of the three dimensions, the original model's factors and extensions used in later studies are presented.

Technology

The technological context deals with a technology's availability and its characteristics (DePietro et al., 1990).

Availability comprises the internal and external technologies that are relevant to the firm (i.e., those already in use by the firm and those available in the marketplace but not currently in use). The existing technologies limit the scope and pace of technological change. Similarly, technologies not yet in use affect innovation by demonstrating which technology options can be adopted and simultaneously demarcating the limits of the technology to be invented as those technologies not yet invented can apparently also not be adopted (Baker, 2012).

The technologies outside the firm's boundaries can be further divided into three characteristics or types of innovation: those that create incremental, synthetic, or discontinuous changes (Tushman and Nadler, 1986). Innovations that cause incremental change include new versions of existing technologies or new features and thus bear the lowest levels of risk and change. Synthetic innovations cause a moderate change by combining existing ideas or technologies in novel ways (Baker, 2012). Finally, innovations that produce a discontinuous change represent significant deviations from existing technology or processes and are therefore defined as radical innovations (Ettlie, Bridges, and O'Keefe, 1984). The types of innovation that firms are exposed to also define the success factors in technological change, and thereby the competitive standing (e.g., pace of adoption). Moreover, radically innovative technologies can be distinguished between an either competence-enhancing or competence-destroying effect (Tushman and Anderson, 1986). The former type of innovation (e.g., RFID technology) brings gradual change as companies expand their expertise. By contrast, the latter type of innovation (e.g., Cloud computing) may render existing technologies and expertise superfluous; it often causes major shifts in industries (Baker, 2012).

Organizations must therefore carefully consider the technology availability and the corresponding type of organizational changes that will be caused by its adoption (Baker, 2012).

As indicated in Section 4.1.2.1, later studies have added further measures for the technological context beyond the original model's factors (availability and characteristics of the technology). According to the literature review conducted by Baker (2012), statistically significant measures include complexity (Grover, 1993), trialiability (Ramdani, Kawalek, and Lorenzo, 2009), compatibility (Grover, 1993), technology readiness (Zhu, Kraemer, Xu, and Dedrick, 2004), technology integration (Zhu, Kraemer, and Xu, 2006), technology competence (Zhu and Kraemer, 2005), perceived barriers (Chau and Tam, 1997), perceived benefits (Kuan and Chau, 2001; Lee and Shim, 2007), and relative advantage (Ramdani et al., 2009).

Organization

The organizational context encompasses the characteristics and resources of the firm. The original model uses linking structures between employees, intra-firm communication processes, firm size, and slack resources to account for organizational influences on technology adoption (DePietro et al., 1990).

Linking structures, i.e., mechanisms that connect subunits of an organization or span internal boundaries (e.g., informal linking agents, cross-functional teams), foster innovation (Tushman and Nadler, 1986). In addition to linking structures, the overall organizational structure also affects the adoption process. Organic organizational designs with decentralized organizational structures (e.g., high emphasis on teams, changing responsibilities for employees, promotion of lateral communication) are linked to adoption (Burns and Stalker, 1994). Mechanistic structures (e.g., formal reporting relationships, centralized decision-making, and clearly defined roles for employees), by contrast, are better suited to the implementation phase rather than the adoption phase (Zaltman et al., 1973).

Communication processes are a further promotor or inhibitor of innovations. Top management behavior, especially, can foster innovation by creating a stimulating atmosphere that welcomes change and is supportive of innovations (Tushman and Nadler, 1986). Facilitating elements encompass "describing the role of innovation within the organization's overall strategy, indicating the importance of innovation to subordinates, rewarding innovation both formally and informally, emphasizing the history of innovation within a firm, and building a skilled executive team that is able to cast a compelling vision of the firm's future" (Baker, 2012, p. 234).

The amount of slack resources is another innovation-affecting factor in the organizational context. However, slack's correlation to innovation adoption remains inconclusive (Baker, 2012). Contradicting findings from previous research are brought together in the work by Nohria and Gulati (1996), who propose an inverse U-shaped relationship between organizational slack and innovation. Put differently, "both too much and too little slack may be detrimental to innovation" (Nohria and Gulati, 1996, p. 1245).

The link between an organization's size and innovation adoption is also inconclusive (Baker, 2012). The often-observed positive relationship between size and adoption (Cyert and March, 1963; Kamien and Schwartz, 1982; Scherer and Ross, 1990) is weakened by the critique that size is a too generic proxy (Kimberly, 1976).

In his literature review, Baker (2012) presents further factors of the organizational context that reveal statistically significant results, such as satisfaction with existing systems (Chau and Tam, 1997), strategic planning (Grover, 1993), top management support (Grover, 1993; Ramdani et al., 2009), presence of champions (Grover, 1993; Lee and Shim, 2007), support infrastructure (Grover, 1993), perceived financial cost (Kuan and Chau, 2001), financial resources (Zhu et al., 2004), financial commitment

(Zhu and Kraemer, 2005), perceived technical competence (Kuan and Chau, 2001), organizational readiness (Ramdani et al., 2009), business scope (Zhu, Kraemer, and Xu, 2003; Zhu and Kraemer, 2005) as well as different aspects of firm or business size (Thong, 1999; Zhu et al., 2003; Zhu et al., 2006; Zhu et al., 2003).

External task environment

The external task environment or environmental context includes industry characteristics and market structure, technology support infrastructure, and government regulation (DePietro et al., 1990).

In past research, different perspectives have been taken to study the effect of industry structure on innovation. One study, for example, posits that fierce competition fosters adoption (Mansfield, 1968). In another, dominant firms can use their power to exert pressure on other value chain partners, forcing them to innovate (Kamath and Liker, 1994). Firms in rapidly growing industries, in early stages of the industry life cycle, tend to innovate faster. In contrast, how innovation is affected is not clear-cut in mature or declining industries (DePietro et al., 1990). On the one hand, the decline of an industry can compel organizations to increase efficiency through innovative solutions. On the other hand, efforts to reduce costs may lead to the reduction of innovation-related investments (Baker, 2012).

Another influencing factor of innovation adoption is the support infrastructure for technology (Baker, 2012). For labor-intensive companies that have to pay high wages for skilled personnel, innovation is a means for reducing costs (Levin, Levin, and Meisel, 1987). The availability of skilled labor, as well suppliers of technology services, are also innovation-facilitating factors (Rees, Briggs, and Hicks, 1984).

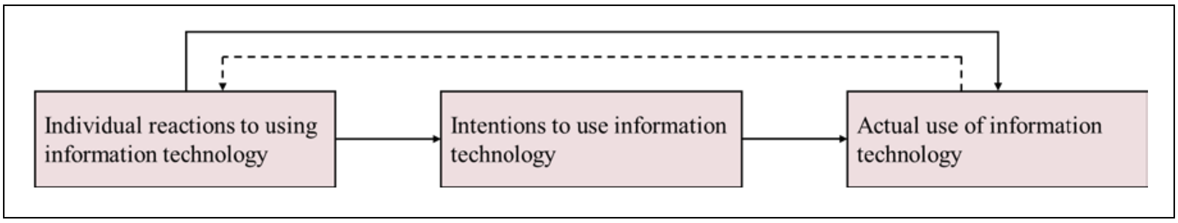
Finally, the regulatory environment's effect can be either beneficial or detrimental, depending on its specific context. On the one hand, the imposition of constraints can require progressive solutions that foster innovation. On the other hand, regulations that restrict a company's options can retard innovation (Baker, 2012).

Other variables of the environment context presented by Baker (2012) that lead to significant results in later studies include management risk position (Grover, 1993), role of IT (Grover, 1993), adaptability of the innovation (Grover, 1993), perceived industry or competitive pressure (Kuan and Chau, 2001; Zhu et al., 2003), performance gap (Lee and Shim, 2007), market uncertainty (Lee and Shim, 2007), perceived government pressure (Kuan and Chau, 2001), and regulatory support (Zhu and Kraemer, 2005).

4.1.3 Adoption at the individual level

After the discussion of adoption theories at the organizational level, this section examines adoption research on the individual employee level. The overwhelming majority of adoption theories are focused on the individual level (Yu and Tao, 2009). These theories often follow a basic scheme (see Figure 4.3): The models test different individual reactions to and perceptions of the IT system or solution, which leads to an intention towards the use that, in turn, results in the actual usage behavior. Whilst numerous models employ intentions as a predictor of actual behavior, few theories directly measure usage (Venkatesh et al., 2003).[80]

Figure 4.3: Basic concept of adoption theories at the individual level



Source: Own illustration based on Venkatesh et al. (2003)

4.1.3.1 Discussion of individual adoption theories

The greatest differences between the various models, however, lie in their selection of determinants of intention and/or usage. The theory employed in this thesis is selected based on these adoption factors, but also contextual considerations (e.g., applicability in a professional environment) and model specifics (e.g., variance explained).

The theory selected as the model of choice for the empirical investigation among the original models and their extensions (e.g., DTPB, TAM2, TAM3, UTAUT2)[81] is the UTAUT. This model is selected for three reasons. First, the UTAUT constitutes a

[80] See Sheppard, Hartwick, and Warshaw (1988) for an extended review of the relationship between intention and behavior.

[81] Note that this thesis does not cover the various minor modifications the models have undergone to suit the purposes of the particular studies in which they have been used.

comprehensive model that integrates a multitude of previous adoption models. With the development of the integrated acceptance model UTAUT, Venkatesh et al. (2003) react to the "proliferation of competing explanatory models of individual acceptance of information technology" (p. 471). It therefore evades having to "'pick and choose' constructs across the models, or choose a 'favored model' and largely ignore the contributions from alternative models" (Venkatesh et al., 2003, p. 426). In their meta-analysis, they conceptually and empirically compare fourteen different constructs from eight acceptance theories and their extensions (TAM/TAM2, TRA, C-TAM-TPB, TPB/DTPB, MPCU, IDT, MM, and SCT) (Venkatesh et al., 2003). The researchers develop and empirically validate the UTAUT based on this analysis. Their motivation to develop a unified theory is grounded in the similarities of many constructs of existing theories, which Venkatesh et al. (2003) logically map and consolidate (Williams, Rana, and Dwivedi, 2012). In addition, UTAUT is suitable for the context of this dissertation due to its specific IT focus, its primary application in organizational settings, its validity in both mandatory and voluntary[82] settings, and that its non-reciprocal nature allows for a cross-sectional research design. Furthermore, much of the criticism regarding other models (see Table 4.3) does not apply to UTAUT. In addition to the aforementioned aspects, it granularly measures intention and use, possesses sufficiently operationalized constructs that still leave room for context-specific modifications, and can also explain past behavior (i.e., does not have a merely predictive character). Moreover, it has been used in a considerable number of studies. Finally, UTAUT makes it possible to explain a notably higher proportion of behavioral intention variance (69% and 70%, respectively) and thus, outperforms the eight previous models (between 17% and 53%) (Venkatesh et al., 2003).

[82] Moore and Benbasat (1991) define voluntariness of use as "the degree to which use of the innovation is perceived as being voluntary, or of free will" (p. 195). The variable therefore takes into account the perceived degree of freedom, which – even in non-mandatory settings – may be curtailed through corporate policies and organizational behaviors. For instance, perceived complexity might not hinder the adoption in a mandatory environment, whereas it may discourage prospective adopters in a voluntary setting (Hossain and Quaddus, 2015). For this study, the distinction of the nature of use is important even though the use of data analytics in FDD is not regulated and is commonly not mandated by the firm's management. However, depending on the management's directives, the adoption may be perceived as either voluntary or mandatory.

Table 4.3: Critique of individual technology adoption theories

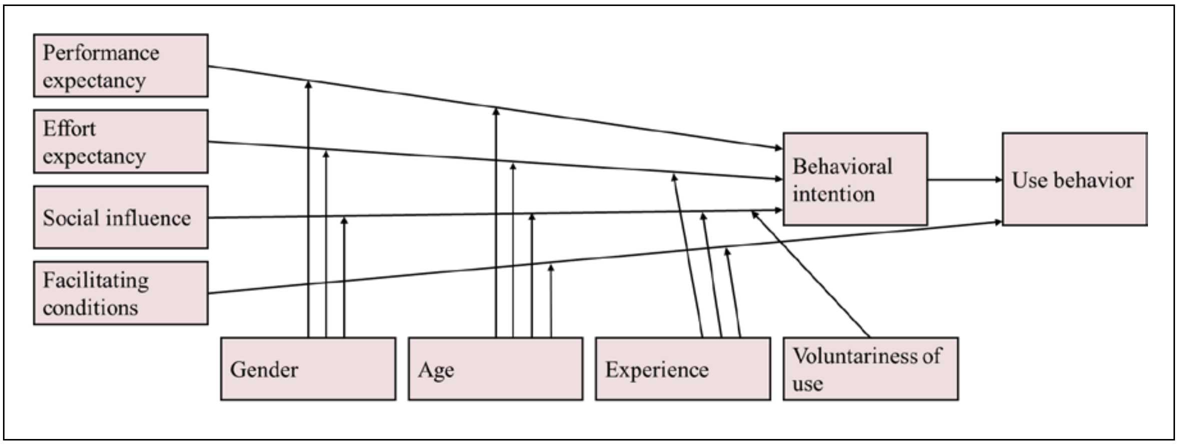
Theory/model	Main critique
Theory of Reasoned Action (TRA)	• The theory is broadly defined and **does not specifically address technology decisions**. For instance, it concentrates on behavioral and normative beliefs and thus **neglects to address the roles of factors** such as interpersonal relations, which may be of importance in the adoption or rejection of a new technology (Ajzen, 2002; Moody and Siponen, 2013). • The **attitude construct** has been criticized in recent studies for its **low explanatory power** (Jokonya, 2017). • The theory is primarily **designed for voluntary behavior** and best suited for a volitional context, which commonly does not hold true for the examination of technology adoption in an organizational setting (Ajzen, 1985; Gallivan, 2001). Such contexts usually require different factors such as specific resources and skills (Gagnon, 2006). • It has a merely **predictive character**, but does not explain past behavior (Högg, 2010).
Theory of Planned Behavior (TPB)	• The TPB possesses some weaknesses analogous to those of the TRA, such as the **lack of important influence factors** (Ajzen, 2002) and the **predictive, non-explanatory character**.
Theory of Interpersonal Behavior (TIB)	• The TIB intends to improve upon prior models through a wider scope that includes cultural, social, and moral factors. This attempt, however, **lacks sufficiently operationalized variables** and thus **raises complexity** that, in turn, lead to a **lack of applicability** (Gagnon, 2006). • Thus, only **few empirical studies** that make use of the TIB can be observed.
Technology Acceptance Model (TAM)	• Analogously to prior intention-based theories, the TAM **neglects limitations of volitional decisions** such as time-related, environmental, or organizational restrictions as well as unconscious habits (Bagozzi, Davis, and Warshaw, 1992; Lee, Kozar, and Larsen, 2003). • The **introduced constructs** of perceived usefulness and perceived ease of use are **not sufficiently described** in the original model and need to be refined (Adams, Nelson, and Todd, 1992). • This leads to one of the most common criticisms of the TAM, its **lack of actionable guidance to practitioners** (Lee et al., 2003). • The model's simplicity is viewed as a strength of the TAM. Yet, on the other hand, the model **needs to be extended by further variables to avoid oversimplification** and to fit the different technologies, situations, and individuals it investigates (Bagozzi, 2007).
Technology Acceptance Model 2 (TAM2)	• Although the TAM2 achieves good progress in the elaboration of mediating variables and underlying causes of one main predictor of intention (perceived usefulness), it **does not integrate the factors that have an influence that is mediated by the perceived ease**.
Technology Acceptance Model 3 (TAM3)	• Based on its advanced spectrum of determinants, the model **does not leave sufficient room to tailor it to the particular context** (Venkatesh and Bala, 2008) in order to gain context-specific rather than generic insights.
Decomposed Theory of Planned Behavior (DTPB)	• Overall, the model's statistical power for behavior is on a similar level as in the TPB and TAM (Smarkola, 2008). The slight increase of predictive power of behavior by 2% (compared to the TAM) does not adequately justify the **increased complexity** and the resulting **subsiding parsimony** (Smarkola, 2008).
Combined Technology Acceptance Model and Theory of Planned Behavior (C-TAM-TPB)	• The C-TAM-TPB is **usually known as an input model** for the UTAUT than as a widely used independent framework. • Consequently, it **lacks considerable previous empirical applications**.
Model of Personal Computer Utilization (MPCU)	• As its name suggests, the MPCU is **specifically tailored to the use of personal computers** (Thompson et al., 1991). • The MPCU is **solely applicable in voluntary settings** (Thompson et al., 1991). • It **only explains 24% of the variance** on utilization (Thompson et al., 1991).

	• Two of the proposed factors do **not have a significant influence** on utilization (Thompson et al., 1991).
Social Cognitive Theory (SCT)	• In the context of technology adoption research, the SCT has **oftentimes been reduced to the concept of self-efficacy**, whilst neglecting important constructs such as outcome expectations and emotional factors (Carillo, 2010). • The SCT underlies the premise that individuals can influence their actions in a **self-contained manner**, which does **not necessarily hold true** in this study **due to potential employer-related requirements** (McCormick and Martinko, 2004). • The **reciprocal nature** of SCT requires the consideration of time-related developments in the individuals' learning process that would be best captured in a **longitudinal** rather than a cross-sectional study (Carillo, 2010) as is planned in this thesis.
Motivational Model (MM)	• Igbaria et al. (1996) admit that for some of the proposed linkages among the variables of the MM, there is **only moderate support**. • They also confess that their model **only explains 28% of the variance** on usage (Igbaria et al., 1996). • The model by Igbaria et al. (1996) **lacks tests on potential interaction effects**.
Task-Technology Fit Theory (TTF)	• Despite its contingent nature, the TTF **lacks to cover organizational and environmental factors** (Furneaux, 2012).
Unified Theory of Acceptance and Use of Technology (UTAUT)	• The construct of **social influence does not cover the unnoticed part**, which is taken for granted. It covers the direct influence of significant colleagues, subordinates, and organizations, but does not refer to the overall normative structure of the organization or its perception. • The construct of **facilitating conditions does not include the compatibility with** individual, team, or organizational **values and goals**.
Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)	• By extending the original UTAUT by the three constructs of hedonic motivation, price value, and habit, UTAUT2 aims at the application in the **consumer context** (Venkatesh et al., 2012).
Innovation Diffusion Theory (IDT)	• The strong abstraction with the **dichotomy between adoption and rejection** of an innovation systematically **prevents the granular analysis** of different levels of IT usage and of important context factors in the individual takeover process (Bayer and Melone, 1989; Karnowski and Kümpel, 2016). • The model **lacks specificity** as it is developed to examine the diffusion of any type of innovation (Chau and Tam, 1997; Gallivan, 2001). • **Not necessarily all stages** of the decision-making process proposed by IDT **are passed** for an innovation (Lyytinen and Damsgaard, 2001). • Large parts of IDT were developed in the **context of voluntary acceptance** or rejection of an innovation based on the expected benefits and do not sufficiently consider settings in which IT adoption is encouraged by management (Leonard-Barton and Deschamps, 1988) or compulsory (Moore and Benbasat, 1991).

Source: Own illustration

In their development of the UTAUT, Venkatesh et al. (2003) identify four significant constructs: effort expectancy, performance expectancy, social influence, and facilitating conditions. While the first three constructs affect behavior indirectly (via intention), facilitating conditions have a direct influence on behavior (see Figure 4.4). Furthermore, the model contains four moderating variables: gender, experience, age, and voluntariness of use (Venkatesh et al., 2003). These variables play a crucial role, as all key relationships in the UTAUT are moderated.

Figure 4.4: Unified Theory of Acceptance and Use of Technology



Source: Own illustration based on Venkatesh et al. (2003)

4.1.3.2 Unified Theory of Acceptance and Use of Technology

After the brief introduction to UTAUT in Section 4.1.3.1, this subchapter describes the model's key components (performance expectancy, effort expectancy, social influence, facilitating conditions) and moderators (gender, age, experience, voluntariness of use) in more detail. Overall, all key constructs receive strong empirical support from prior studies as outlined in two meta-analyses of 27 and 174 quantitative investigations of the UTAUT, respectively (Dwivedi, Rana, Chen, and Williams, 2011; Williams, Rana, and Dwivedi, 2015).

Performance expectancy

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). The construct consists of five determinants from previously developed theories that all have similar meanings: perceived utility (TAM, TAM2, and C-TAM-TPB), extrinsic motivation (MM), job fit (MPCU), relative advantage (IDT), and outcome expectations (SCT) (Venkatesh et al., 2003).

The expected gains in task performance are the strongest predictor of behavioral intention for both voluntary and mandatory settings (Venkatesh et al., 2003). Prior empirical studies reveal that age and gender moderate the relationship between performance expectancy and intention to use. According to Venkatesh and Morris (2000) and Venkatesh et al. (2003), performance expectancy is particularly salient to men. They refer to a study by Minton and Schneider (1980) that posits that, reinforced from birth, men tend to be more task-oriented than women and thus have a stronger focus on task accomplishment. Studies from the psychology domain reveal that although gender roles are relatively permanent, they are open towards change over time (Kirchmeyer, 2002). Given the publication dates of the aforementioned studies, the moderating role of gender as reflected in the UTAUT model may not represent the current state of research and therefore requires an update by future studies. In addition to gender, age represents a significant moderating variable in the original UTAUT (Venkatesh et al., 2003). Prior research shows that younger employees tend to assign more value to extrinsic incentives (Hall and Mansfield, 1975). It is theorized, and empirically validated, that junior staff are more receptive to new technologies as soon as they recognize performance improvements brought about by an adoption (Morris and Venkatesh 2000; Venkatesh and Morris 2000; Venkatesh et al., 2003).

Effort expectancy

Effort expectancy refers to "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). It captures the concepts from three similar constructs employed in previous models: perceived ease of use (TAM and TAM2), complexity (MPCU), and ease of use (IDT) (Venkatesh et al., 2003).

Effort expectancy has a significant influence on both voluntary and non-voluntary contexts (Venkatesh et al., 2003); yet, its influence decreases over time. In particular, initial processual obscurities lead to a higher salience of effort expectancy in the early stages. Later, instrumental concerns tend to come to the fore (Davis et al., 1989; Szajna, 1996; Venkatesh, 1999). According to the original UTAUT, effort expectancy is moderated by gender, age, and experience (Venkatesh et al., 2003). The effects of gender and age are diametrically opposite to those observed for performance expectancy. Effort expectancy is more pronounced for older women than for younger men (Morris and Venkatesh, 2000; Venkatesh and Morris, 2000; Venkatesh, Morris, and Ackerman, 2000; Venkatesh et al., 2003). According to Motowidlo (1982), the gender effect traces back to cognitive factors rather than gender roles. Moreover, older employees attach more importance to easy-to-use technology (Morris and Venkatesh, 2000; Venkatesh et al., 2003). Prior research shows that older co-workers are more likely to experience difficulties concentrating on and processing complex information (Plude and Hoyer, 1985); capabilities required for various technological innovation in the professional context (Venkatesh et al., 2003). In addition to gender and age, experience moderates the relation between effort expectancy and behavioral intention. Less experienced co-workers have a higher value for simple and effortless IT solutions (Venkatesh et al., 2003).

Social influence

Social influence means “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, p. 451). The construct consists of three variables from other adoption theories: subjective norm (TRA, TAM2, TPB, DTPB, and C-TAM-TPB), social factors (MPCU), and image (IDT) (Venkatesh et al., 2003).

The relationship between social influence and behavioral intention is simultaneously affected by four moderating variables: voluntariness, gender, age, and experience (Venkatesh et al., 2003). Similarly to its components from former adoption theories, the social influence construct is only statistically significant in the early adoption stages in mandatory settings (Hartwick and Barki, 1994; Venkatesh and Davis, 2000; Venkatesh et al., 2003). In such contexts, prospective adopters try to act compliant, i.e., in line with the directives of socially influential people who can issues rewards or punishments based on compliance with the desired behavior (e.g., using a new technology) (Hartwick and Barki, 1994; Venkatesh and Davis, 2000; Warshaw 1980). This social pressure tapers off over time as the prospective adopters’ experience and knowledgeability and subsequent ability to form an individual intention increase (Venkatesh et al., 2003). Individual beliefs come to the fore with the increasing degree of knowledgeability as well as in voluntary settings. In such situations, social influence does not have a significant impact on behavioral intention (Venkatesh and Davis, 2000; Venkatesh et al., 2003). Another moderating variable of social influence is gender. In line with theoretical considerations, empirical evidence suggests that women are more receptive to social influence when they develop an intention to use a new technology. According to Venkatesh et al. (2000), this is due to their higher awareness of the opinions of others. Age also plays a decisive role in the moderation of social influence. Older employees have greater affiliation needs, which lead to a higher degree of social influence (Morris and Venkatesh, 2000; Venkatesh et al., 2003). The effects of both gender and age on technology adoption decline with experience (Morris and Venkatesh, 2000; Venkatesh and Morris, 2000; Venkatesh et al., 2003).

Facilitating conditions

Facilitating conditions represent “the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system” (Venkatesh et al., 2003, p. 453). This construct is derived from three measures used in previous theoretical models: perceived behavioral control (TPB, DTPB, and C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT) (Venkatesh et al., 2003). All of these determinants focus on the mitigation or removal of technological and organizational barriers (Venkatesh et al., 2003).

Under the presence of both the performance expectancy and effort expectancy constructs, facilitating conditions do not have a significant influence on the intention to use (Venkatesh et al., 2003). Venkatesh et al. (2003) explain this observation stating, “that issues related to the support infrastructure – a core concept within the facilitating conditions construct – are largely captured within the effort expectancy construct which taps the ease with which that tool can be applied” (p. 453). In contrast, facilitating conditions have a direct influence on actual use that is not mediated by behavioral intention (Venkatesh et al., 2003). This effect is moderated by two variables: age and experience (Morris and Venkatesh, 2000; Venkatesh et al., 2003). With increasing usage experience, employees identify where to seek support in their organizations and can leverage that support to remove barriers to sustained use (Bergeron, Rivard, and De Serre, 1990; Venkatesh et al., 2003). Analogous to experience, age has a positive moderating effect. Older employees assign a higher value to the support infrastructure since they are more likely to experience cognitive and physical limitations (Hall and Mansfield, 1975; Morris and Venkatesh, 2000).

4.2 Adoption of data analytics in finance and accounting – A literature review

This section provides a literature-based overview of adoption of data analytics and related technologies in audit firms, which typically also conduct FDD (see Section 2.2.3.4). Adjacent literature from the finance and accounting domain is employed due to a lack of M&A-specific literature (see Section 3.3). The section first provides insights on the level of adoption of data analytics (Section 4.2.1). This part also includes related technologies, which make it possible to draw inferences on data analytics adoption. Subsequently, the different organizational (Section 4.2.2) and individual (Section 4.2.3) adoption factors specific to the field of accounting are presented and, since large parts of earlier research are not based on a particular adoption model, assigned to constructs of the selected theories.

4.2.1 Level of adoption

Historically, audit firms have been slow adopters of emerging technologies despite conducting business activities that are "prime for partial automation due to [their] labor intensiveness and range of decision structures" (Issa et al., 2016, p. 1) (see also Alles, 2015; Alles and Gray, 2016; Bierstaker, Janvrin, and Lowe, 2014; Dai and Vasarhelyi, 2016; Richins et al., 2017). In addition to technologies, audit firms have also shown modest adoption behavior towards the inclusion of non-financial data (Alles and Gray, 2016). Cockcroft and Russell (2018) characterize the lack of adoption of both emerging technologies and new data sources as a paradox since the finance and accounting disciplines are traditionally accustomed to handle large volumes of data. This delay in adoption can partially be attributed to the industry's "conservatism and rigidity" (Dai and Vasarhelyi, 2016, p. 2). Oftentimes, audit firms have fallen short of expectations and lagged behind their clients in adopting technological advancements (Alles, 2015). Studies by Alles and Gray (2016) and Appelbaum et al. (2017) describe how clients' internal audit functions are ahead of external auditors in the use of big data and analytics. Furthermore, Appelbaum et al. (2017) point out that clients' increasing use of big data, as well as the subsequent application of advanced analytics, challenge the traditional work of audit firms.

There is, however, ample evidence that audit firms, in particular the Big Four, have begun to react and adapt to the advent of big data and data analytics in their core business – auditing (Earley, 2015; Gepp et al., 2018; Issa et al., 2016; Richins et al., 2017; Salijeni et al., 2019). Kokina and Davenport (2017) and Richins et al. (2017) provide concrete examples of their activities, such as Deloitte's partnership with Kira Systems[83] and its development of the data analytics solution Optix, KPMG's partnership with IBM,[84] EY's plans to use big data and blockchain in the financial statement audit, and PwC's efforts in automated audit technology (e.g., the analytics platform Halo). Despite publicly announcing such investments, the "true extent of [the] use in

[83] The partnership is for developing the machine learning-based text mining software Argus that enables quick extraction of information from unstructured documents (e.g., contracts), which shall be used in the audit and consulting practices (Richins et al., 2017).

[84] The partnership allows KPMG to use IBM's cognitive computing technology Watson to facilitate audit processes that rely on judgement (Kokina and Davenport, 2017; Richins et al., 2017).

practice is unknown and would be [the] subject of valuable future research" (Gepp et al., 2018, p. 18).

Some studies reveal differences between, and within, the accounting firms. Salijeni et al. (2019) outline differences between Big Four and non-Big Four firms and ascertain that the Big Four firms' investments have been used to either acquire or self-develop data analytics tools. In contrast, smaller audit firms mainly use off-the-shelf analytics software. Moreover, Rosli et al. (2013) find that small and medium-sized audit firms use fewer and less advanced tools than larger audit firms. These differences in analytics investments and use may be caused by the differences between the Big Four and smaller audit firms with regard to financial resources, organizational slack, client IT complexity, and client expectations (Janvrin et al., 2008; Lowe et al., 2017; Riemenschneider, Harrison, and Mykytyn, 2003; Rosli et al., 2013).

In addition to differences between firms, there are also disparities within accounting firms across their various service lines. In terms of both investment focus and pace of adoption of data analytics, the advisory or consulting practices are ahead of the more traditional auditing and tax business (Earley, 2015). Earley (2015) ascribes this observation to two factors: the liability concerns as well as the highly regulated environment of auditing (see also Alles and Gray, 2016).

Across different firm sizes and service lines, researchers have observed a gradual shift towards the inclusion of big data and towards the use of data analytics tools. For instance, Kim, Mannino, and Nieschwietz (2009) report that basic features (e.g., database queries and ratio analysis) are more accepted than advanced features (e.g., regression, variance analysis, and classification) among auditors (see also Mahzah and Lymer, 2014). Similarly, Alles and Gray (2016) refer to a successive shift towards the inclusion of big data and write that "auditors can develop their analytical skill[s] by first using data similar to familiar accounting variables […] and then expand outward" (p. 52).

In summary, public accounting firms traditionally lag behind other industries in incorporating non-traditional data sources and introducing technological advancements such as analytics tools. In recent years, however, the Big Four in particular have made publicized investments in (big) data analytics technologies and have begun to gradually shift towards the use of data analytics. Unlike smaller audit firms that rely on standard software, the Big Four have used their financial resources to establish partnerships with technology companies and develop proprietary software. Aside from these differences between companies, previous research also reveals gaps within professional service firms: the advisory business is more inclined to adopt technology than the auditing and tax service lines. These findings, however, mainly stem from auditing research. As part of this thesis, findings are transferred to FDD.

The following two sections provide an overview of the various organizational and individual adoption factors reported in prior literature regarding IT (and especially analytics) adoption by audit firms. Of note, Dagiliene and Kloviene (2019) describe prior research on data analytics in external auditing as fragmented, limited, and incomplete. It must also be considered that the vast majority of previous literature is qualitative in nature and does not follow a selected theoretical adoption model. It therefore follows that the influence factors are linked to the main constructs of the TOE framework and UTAUT as part of this analysis.

4.2.2 Organizational adoption factors

The overview of organizational adoption factors is structured along the dimensions of the TOE framework: technology, organization, and external task environment.

Technology

Audit firms' decisions to adopt a new technology, such as the various analytics tools, must be reasoned from a financial stance. However, the cost-benefit ratio of such investments is not clear-cut. In an interview-based analysis with decision-makers in the auditing domain, Mahzah and Lymer (2014) find that perceived benefits have a substantial impact on the adoption decision. According to their study, the main benefits perceived include cost savings, a greater scope that can be covered, increased quality, and faster processing time. On the one hand, the companies can generate cost advantages through (partial) automation of manual, repetitive tasks that are commonly conducted by entry-level employees (Richins et al., 2017). On the other hand, the benefits of an increased process speed and decreased labor efforts are often not accompanied by revenue gains due to the traditional bill-by-hour approach (Issa et al., 2016). Put differently, the introduction of an efficiency-enhancing technology may only be beneficial when the cost savings surpass previous investments and potential revenue losses resulting from decreases in the number of hours billed.

Next, as proposed in the original TOE framework, the availability of technology plays a major role in audit firms' decision-making processes. The increased availability, commoditization, and affordability of software, databases, and web platforms also enables non-Big Four firms to adopt such IT solutions in spite of their comparatively weaker financial resources (Alles, 2015; Lowe et al., 2017). For instance, smaller audit firms use "off-the-shelf analytics software such as Spotlight, Lavastorm, and Alteryx" (Salijeni et al., 2019, p. 5) instead of developing analytics capabilities in-house (Alles, 2015).

Organization

From an organizational perspective, the most frequently mentioned adoption factor is firm size, which is characterized by a higher adoption by the Big Four as compared to their non-Big Four competitors (Janvrin et al., 2008; Lowe et al., 2017; Rosli et al., 2013). Larger size is associated with the substantial financial resources necessary to finance investments (Dagiliene and Kloviene, 2019; Janvrin et al., 2008; Lowe et al., 2017) and the organizational slack to use these resources (Lowe et al., 2017). The divergence of IT adoption between the Big Four and smaller audit firms has lessened due to the increased availability of affordable standard software (Lowe et al., 2017); however, differences in the actual use remain. While small and medium-sized audit firms rely on basic features, large companies utilize more advanced tools (Rosli et al., 2013). This observation reveals that differences in firm size affect the actual software use (*how*) rather than the adoption decision (*what*).

Another relevant intra-organizational aspect is potential benefits resulting from knowledge-sharing and tool-sharing in instances where analytics is used across multiple service lines (Alles, 2015). For example, the adoption of data analytics in FDD may be fueled by positive experiences with analytics usage and built expertise in other service lines.

External task environment

In the environmental context, the client situation, current and potential competitors, as well as regulatory and legal factors, play a key role in making the adoption decision.

With respect to client perception, the question arises whether analytics adoption by audit firms is a demand-driven or supply-driven decision (Alles, 2015). On the one hand, some clients themselves rely on big data and analytics tools in their businesses (e.g., in marketing, product development, operational strategies) and thus, also in their financial estimates and income statements (Alles, 2015). These clients therefore might expect their auditors and financial advisors to use the same data and technologies.[85] Furthermore, Lowe et al. (2017) report that companies with a greater IT complexity have higher IT needs and thus are receptive towards audit firms using advanced technologies; however, this argument only holds true when clients possess mature analytics capabilities. Kreher and Gundel (2018) assert that most companies still rely on basic digital solutions in their accounting functions and rarely harness (big) data analytics and visualization tools. In line with this argumentation, Gepp et al. (2018) note that "auditors are reluctant to use techniques and technolog[ies] that are far ahead of those adopted by their client firms" (p. 2). In sum, demand-driven decisions are likelier to be made by those audit firms with IT-oriented clients. On the other hand, Mahzah and Lymer (2014) posit that the use of certain technology on client projects by external auditors influences the adoption of that technology by those clients' internal audit functions. This speaks in favor of the supply-driven decision-making approach. Kreher and Gundel (2018) underscore the ambiguous role of client demand with the statement that "more than 45 percent" (p. 17) of the companies surveyed expect their auditors to increase efficiency, use big data analytics, cognitive systems, modern visualization techniques, and benchmarking.

In terms of competition, both new entrants and established players influence adoption decisions. In addition to competition from established audit firms (Lowe et al., 2017), potential competition from non-audit firms needs to be taken into account. Such new entrants, in particular, include technology-based firms with competitive advantages in data analysis, such as accounting technology start-ups (so-called "AccTech", Richins et al., 2017, p. 33). Such competitive pressure fosters the need to innovate and to adopt new technologies.

Another key factor in adoption decisions is the availability of skilled and trained personnel (Issa et al., 2016; Salijeni et al., 2019). In particular, the use of analytics requires skills in the areas of IT, statistics, and modeling, which are not part of the current education of auditors and consultants (Appelbaum et al., 2017). This situation

[85] Related to big data, Alles (2015) underscores this view stating, "that the most likely driver of the use of [b]ig [d]ata by auditors is client use of [b]ig [d]ata" (p. 442).

creates the need for both hiring skilled labor (e.g., data scientists) and training current employees (Issa et al., 2016); however, data specialists commonly have little functional and business knowledge (Salijeni et al., 2019). This creates the need for agents that coordinate the discussions between functionally-focused consultants (e.g., FDD advisors) and technically-oriented co-workers (e.g., data scientists).

Finally, the regulatory and legal environment influences audit firms' adoption decisions (Alles and Gray, 2016). While regulations may have an impact on the auditing discipline (Alles and Gray, 2016; Earley, 2015), the conduct of FDD is less exposed to regulatory restrictions. However, liability concerns (Alles and Gray, 2016; Earley, 2015; Warren et al., 2015) may hold true for both areas. The use of larger amounts of data and the conduct of more detailed analyses with data analytics software may lead to a greater expectation towards the detection of red flags. In turn, missing such abnormalities in the red flag report might have more severe consequences for audit firms.

The factors identified in earlier research that affect the decisions of audit firms to adopt analytics techniques and technologies are presented in Table 4.4.

Table 4.4: Organizational adoption factors for analytics in audit firms – A literature-based overview

TOE core constructs	Adoption factors	Description	Literature
Technology	Technology availability	Positive effect: increased availability, commoditization, and affordability of IT tools lead to higher adoption, especially among smaller audit firms	Alles, 2015; Lowe et al., 2017; Salijeni et al., 2019
	Technology characteristics	No evidence	-
	Cost-benefit ratio*	Unclear effect: cost savings through (partial) automation of manual, repetitive tasks; however, prior investments are needed and the benefits of increased process speed may not involve revenue gains because of the traditional bill-by-hour approach	Issa et al., 2016; Mahzah and Lymer, 2014; Richins et al., 2017
Organization	Formal and informal linking structures	No evidence	-
	Communication processes (top management support)	No evidence	-
	Firm size (incl. financial resources)	Positive effect: larger firms are better able to finance the use of analytics tools in general and of advanced features in particular	Dagiliene and Kloviene, 2019; Janvrin et al., 2008; Lowe et al., 2017; Rosli et al., 2013
	Organizational slack	Positive effect: more slack resources offer the ability to organizationally entrench the use of analytics tools (e.g., through development and coding, trainings)	Lowe et al., 2017
	Intra-organizational benefits through spillover effects*	Positive effect: use of analytics across different services may offer benefits through knowledge sharing and use of common tools	Alles, 2015
External task environment	Industry characteristics and market structure (competitive situation)	Positive effect: pressure from both established audit firms and new entrants (esp. technology-based firms) promotes adoption	Lowe et al., 2017; Richins et al., 2017
	Client demand*	Unclear effect: indications of client demand for analytics use (especially in IT-oriented companies) vs. reports of proactive adoption by audit firms with subsequent client buy-in	Alles, 2015; Gepp et al., 2018; Kreher and Gundel, 2018; Lowe et al., 2017; Mahzah and Lymer, 2014
	Technology support infrastructure (skilled employees)	Positive effect: a skilled and trained workforce is better able to effectively integrate analytics into its work, i.e., it triggers the adoption decision in the first place	Issa et al., 2016; Salijeni et al., 2019
	Regulatory aspects (liability risks)	Negative effect: use of analytics may create higher expectations towards identification of red flags, i.e., undetected risks might have more severe legal consequences in litigations	Alles and Gray, 2016; Earley, 2015; Warren et al., 2015

Notes:
Adoption factors marked with a star (*) are not part of the original TOE framework.

Source: Own illustration

4.2.3 Individual adoption factors

The overview of individual adoption factors is structured along the dimensions of the UTAUT: performance expectancy, effort expectancy, social influence, and facilitating conditions.

A survey-based investigation of audit software adoption finds support for a positive effect of performance expectancy, effort expectancy, and facilitating conditions[86] on the intention to adopt (Payne and Curtis, 2010, cited in Bierstaker et al., 2014). In contrast, social influence does not play a crucial role in individual adoption behavior. These observations are confirmed by both empirically verified and qualitatively outlined arguments put forth by previous research.

Performance expectancy

Curtis and Payne (2014) highlight that the “usefulness of technology to achieving one’s goals was the most significant predictor of technology acceptance […] in accounting” (p. 311). In turn, the employees’ expectations towards performance and usefulness of analytics solutions depend on a number of factors.

First, due to general technology acceptance and compatibility, the usefulness of analytics solutions depends on the client’s IT affinity (Alles, 2015; Gepp et al., 2018). Second, the availability of data, i.e., access to proprietary and sensitive client data, is a prerequisite for the appropriate use of analytics (Alles and Gray, 2016; Warren et al., 2015). The access may potentially be facilitated by the introduction of the Audit Data Standard (Alles, 2015). Another critical issue to sensibly using analytics tools is data quality (Warren et al., 2015), which is of particular importance with regard to non-financial data that audit firms “have been reluctant to use in the past” (Alles and Gray, 2016, p. 46) because of their unclear validation (Alles and Gray, 2016; Appelbaum et al., 2017).

Finally, the interplay of performance expectancy and effort expectancy must be considered. In a TAM-based investigation, Kim et al. (2009) discern that perceived usefulness (which is similar to performance expectancy (Dwivedi et al., 2011)) is more

[86] Note that, contrary to the original UTAUT, the effect of facilitating conditions is measured on behavioral intention and not on actual usage.

important for the use of basic features, whereas perceived ease of use (which is similar to effort expectancy (Dwivedi et al., 2011)) has a higher influence on adoption when advanced features are used. This result illustrates the need for more advanced skills among employees with rising technological complexity.

Effort expectancy

According to prior research, effort expectancy has a significant impact on adoption by auditors (Payne and Curtis, 2010, cited in Bierstaker et al., 2014). For analytics adoption, the major influence factors for effort expectancy include employees' skills and tool complexity.

The literature makes clear that the traditional education and skills of auditors and consultants do not meet the requirements for the effective use of analytics (Alles, 2015; Alles and Gray, 2016; Appelbaum et al., 2017; Bierstaker et al., 2014; Groß, Kummer, Oberwallner, Sellhorn, and Vogl, 2018; Harder, 2018; Issa et al., 2016; Mackenstedt et al., 2018; Salijeni et al., 2019; Warren et al., 2015). In particular, the necessary skills in the areas of IT, statistics, and modeling are underdeveloped and accounting staff is not used to analyzing big data (Appelbaum et al., 2017). Major firms have recognized this competence gap and have established training programs to upskill their employees (Salijeni et al., 2019). These firms have also hired specialists (e.g., data scientists) to extend their internal know-how (Appelbaum et al., 2017; Salijeni et al., 2019). The analytics specialists not only develop software solutions further, but also work in conjunction with consulting teams (Appelbaum et al., 2017; Mackenstedt et al., 2018). The described upskilling efforts are essential to foster adoption. For instance, Bierstaker et al. (2014) refer to a study of Pennington, Kelton, and DeVries (2006), which reveals that "auditors resist the use […] when they perceive the task at hand is too complex and that adequate training has not been provided" (p. 68). As outlined, the skill gap can be closed through increasing experience with analytics software. Thus, it appears intuitive that experience is found to have a strong moderating effect on effort expectancy: "rising experience decreases any impact of effort expectancy on adoption" (Mahzah and Lymer, 2014, p. 340). However, prior research identifies short-term prioritization of project work (as in the busy season in the auditing field) over trainings as one of the challenges to adoption (Payne and Curtis, 2017).

While audit firms can strive to enhance their co-workers' technical competences, the simplification of data analytics tools, especially for the end-user, can also increase their adoption (Huerta and Jensen, 2017). Easy-to-use tools would allow users to focus more on results than on systems technicalities (Huerta and Jensen, 2017). Dai and Vasarhelyi (2016), however, report a "lack of quality tools" (p. 2), suggesting that current analytics tools are too complicated for traditional accountants (see also Brown-Liburd et al., 2015). The improvements to software usability and the reduction of complexity would therefore facilitate the integration of analytics tools into current processes (Alles, 2015; Kim et al., 2009; Mahzah and Lymer, 2014).

Social influence

Overall, the social aspect tends to be of less importance in individual adoption decisions in the given context. For example, Bierstaker et al. (2014) do not find the social influence variable to have a significant effect. Nonetheless, some cultural aspects of the auditing domain are examined in prior research and must be considered. For instance, Bierstaker et al. (2014) highlight the importance of culture in accounting firms (or their teams), which either encourages or creates impediments to adoption. In general, the audit industry and profession are described as conservative and rigid (Dai and Vasarhelyi, 2016; Liu and Vasarhelyi, 2014). However, this observation may not be par for par transferable to the transaction services departments of accounting firms, which typically conduct FDD.

Facilitating conditions

Bierstaker et al. (2014) indicate that facilitating conditions are positively associated with auditors' IT adoption. In particular, they refer to the technical infrastructure that supports software use. This includes both supporting resources and computer support (e.g., specialized instruction, support center, hotline, and use guidelines) (Bierstaker et al., 2014).

The factors found in previous studies that influence the adoption decisions of individual employees in the audit industry are summarized in Table 4.5.

Table 4.5: Individual adoption factors for analytics in audit firms – A literature-based overview

UTAUT core constructs	Adoption factors	Description	Literature
Performance expectancy	Client's IT affinity	Positive effect: more technically oriented clients tend to have a stronger technology acceptance and are likelier to be amenable to diverse analytics software solutions	Alles, 2015; Gepp et al., 2018
	Data availability	Positive effect: better access to proprietary and sensitive client data is a prerequisite for the appropriate use of analytics	Alles, 2015; Alles and Gray, 2016; Warren et al., 2015
	Data quality	Positive effect: data quality, especially of non-financial data, provides accountants trust to achieve valid results, i.e., supports adoption by depleting concerns	Alles and Gray, 2016; Appelbaum et al., 2017; Warren et al., 2015
Effort expectancy	Technical skills	Positive effect: higher education and competences in technical disciplines (e.g., IT, statistics, and modeling) facilitate adoption	Alles, 2015; Alles and Gray, 2016; Appelbaum et al., 2017; Bierstaker et al., 2014; Groß et al., 2018; Harder, 2018; Issa et al., 2016; Salijeni et al., 2019; Warren et al., 2015
	Training	Positive effect: training programs serve to upskill staff, which, in turn, fosters adoption; hence, the effect of trainings will be particularly strong when co-workers lack relevant skills	Bierstaker et al., 2014
	Technology usability	Positive effect: user-friendly, technically less complex analytics tools increase adoption, especially for technically untrained staff	Alles, 2015; Brown-Liburd et al., 2015; Dai and Vasarhelyi, 2016; Huerta and Jensen, 2017; Kim et al., 2009; Mahzah and Lymer, 2014
Social influence	Culture	No effect: no significant effect identified, although qualitative descriptions suggest that an open atmosphere facilitates adoption, whereas a conservative and rigid mindset inhibits adoption	Bierstaker et al., 2014; Dai and Vasarhelyi, 2016; Liu and Vasarhelyi, 2014
Facilitating conditions	Technical infrastructure	Positive effect: support resources and central knowledge repositories support software adoption	Bierstaker et al., 2014

Source: Own illustration

4.3 Summary

This dissertation follows an adoption approach (as opposed to domestication and diffusion approach) to investigate the adoption of data analytics in FDD. In contrast to all previous adoption studies dealing with an audit context, as well as the vast majority of adoption studies in other contexts, this thesis considers both the organizational and the individual level. This comprehensive view is particularly important because the two levels are intertwined in an organizational context.[87]

Previous research, however, lacks an integrated model due to the different analytical units of the two perspectives. Consequently, this thesis assesses the broad spectrum

[87] In contrast, in consumer market settings the individual is the sole unit of analysis.

of 16 different adoption models and their extensions, and finally selects two of those models for the subsequent empirical investigations. At the organizational level, the TOE framework is chosen due to its flexibility, which is particularly helpful for qualitative research. The framework contains technological, organizational, and environmental aspects from which this thesis can draw inferences on organizations' decisions to adopt. At the individual level, UTAUT, which stands out with the development of constructs from eight predecessor models, its IS context specificity, and its suitability for professional settings, serves as a basis for further investigations. The theoretical model is comprised of the four constructs performance expectancy, effort expectancy, social influence, and facilitating conditions used to explain individuals' adoption behavior.

As in the procedure in Chapter 3, the review of prior adoption studies concentrates on adjacent research veins from the finance and accounting domain, especially the auditing field, due to the absence of M&A or due diligence-specific literature. Research findings on the level of adoption show that audit firms historically start slowly to integrate non-traditional data sources and adopt technological advancements. However, audit companies have started to invest in and gradually shift towards (big) data analytics technologies in the recent past. Intercompany and intra-company differences reveal that these efforts are most advanced in the Big Four and in their advisory services, which corroborates the relevance of this research.

In addition to the level of adoption, prior research is reviewed with respect to adoption factors. Surprisingly, large bodies of adoption research in the auditing context follow a qualitative design without guidance from established adoption theories. For this reason, adoption factors are not only identified but are also linked to the main constructs of the TOE framework and UTAUT. Previous research confirms the theoretical findings with a few exceptions. With regard to the organizational level, for example, the importance of economic criteria, benefits for other business areas through spillover effects of the use of technology, and client demand (audit firms act as service providers) are emphasized in the adoption decision. In addition, the strengths of the effects at the individual level differ from the results of the original model (whereby the structure of the effort expectancy is partly insignificant). Lastly, moderating effects are insufficiently captured in previous research.

The insufficient (or non-existent for FDD) consideration of the adoption of data analytics technologies by the Big Four contradicts the growing practical relevance of this topic. The remainder of this thesis is therefore devoted to the study of adoption to date. To that end, a qualitative and quantitative analysis are used to examine the organizational and individual motives in order to draw conclusions for promoting the use of technology.[88]

[88] As outlined in Sections 1.3 and 4.1.1, respectively, the qualitative analysis covers both the organizational and individual level, whereas the quantitative analysis concentrates on the individual level.

5 Use and adoption of data analytics – A qualitative analysis

The fifth chapter describes the imperative for a mixed methods research design that incorporates qualitative interviews as an essential component and not only as means to prepare subsequent quantitative research. The fundamentals of the chosen methodology (guided expert interviews) and the sample of interview partners are introduced (Section 5.1). Then, interview findings concerning the use of (big) data sources and analytics technology are presented along the different FDD process framework phases and areas of analysis described in Section 2.2.4.2. Moreover, the processual implications and associated consequences for the service providers are explored (Section 5.2). The practical importance for audit firms of further increasing the use of analytics tools becomes evident in the expert interviews. Consequently, the remainder of this chapter is devoted to the topic of adoption. The extent of adoption as well as organizational and individual adoption factors are examined. Hypotheses regarding individual adoption factors expand previous theoretical knowledge and are derived for the subsequent quantitative investigation (Section 5.3). Both sections on the use and adoption of analytics technology, respectively, conclude with a separate summary.

5.1 Foundations of qualitative interview-based research

This dissertation makes use of triangulation across methods as it unifies both qualitative and quantitative research within a mixed methods approach (Flick, 2010; Flick, 2011; Schreier and Odağ, 2010). In this chapter, the use and adoption of data analytics are examined qualitatively. Qualitative methods are characterized by their much more open approach to the research object compared to quantitative methods. This approach can also be altered during the research process (Lamnek and Krell, 2016; Rieker and Seipel, 2006). Moreover, by taking an inductive perspective to answer the research questions it is possible to proceed with the utmost openness towards the object of investigation (Brüsemeister, 2008). Thus, existing theories and models are taken into account, but do not dominate the research process (Goldenstein, Hunoldt, and Walgenbach, 2018; Rieker and Seipel, 2006). The principle of openness and the inductive nature are well-suited to the topic under consideration. Especially for the use of analytics, the rudimentary theoretical knowledge does not allow for the formulation of precise questions, descriptive dimensions, or hypotheses (Mayring, 2010). Thus, an explorative design is selected for the initial qualitative study. It aims to “get as close as possible to the object of research in order to develop new, differentiated questions and hypotheses" [translated from German] (Mayring, 2010, p. 231).

Expert interviews are conducted, either in person or via telephone (Meuser and Nagel, 1991; Meuser and Nagel, 2009). The direct interaction between researcher and research subject makes it possible to solve ambiguities and obtain much more detailed evidence than large-scale surveys (Cooper and Schindler, 2013). The interview instrument thereby allows the researcher to "explore arguments and explanations or obtain detailed descriptions" [translated from German] (Mey and Mruck, 2010, p. 431), which is of particular importance to the research subject at hand. Moreover, response error (Cooper and Schindler, 2013) can be reduced or even avoided.

The interviews were conducted in a semi-structured format using a guide (Gläser and Laudel, 2004; Mey and Mruck, 2010; Raithel, 2008). This form of interview is based on questions derived from existing theoretical considerations (Goldenstein et al., 2018). Since the interview guide is not entirely standardized, questions can be successively adapted based on findings from previous interviews. The catalogue of questions is structured along the four research questions (see Table A.2 in the appendix). On the one hand, this approach enables a structured treatment of the research questions regarding (i) the use along the FDD process model and (ii) the adoption along the theoretical foundation of TOE and UTAUT. On the other hand, it leaves sufficient flexibility to explore aspects outside these structures.

Meuser and Nagel (2009) define experts as people who "carry responsibility for the design, development, implementation, and/or controlling of a solution and with access to privileged information" [translated from German] (p. 470). In the case of FDD, it is sensible to follow the consideration set forth by Sprondel (1979), who sees expert knowledge as tied to the professional role. Consequently, the selected experts work in the transaction services advisory departments or in deals analytics centers of excellence (CoEs) of the large audit firms.[89] In their roles, they need to possess both the functional and technical know-how required to explore the research questions. In

[89] The only exception was an interviewee from the data and analytics consulting division of a Big Four firm whose insufficient functional knowledge of FDD meant the research topic could only be dealt with abstractly. The author subsequently concentrated exclusively on interview partners from the functional core area of FDD.

order to obtain different perspectives, interviews are conducted with people from different hierarchical levels.[90]

The interview partners are selected using snowball sampling (also known as chain sampling) (Schreier, 2010). After initial interviews with leading due diligence practitioners from the author's professional network, further experts are identified through the practitioners' networks. Thus, snowball sampling helps to establish a relatively homogenous group of interviewees (Schreier, 2010). Moreover, according to Schreier (2010), "this approach is particularly suitable for groups of people to whom researchers have difficulty gaining access" [translated from German] (p. 243). Accessing the experts interviewed for this thesis is difficult because their daily work leaves them little time for extra tasks such as interviews. Moreover, the digital transformation of the FDD process represents an emerging and highly sensitive field about which they tend not to share any information. Consequently, interview partners could only be gained after prior assurances of anonymity.

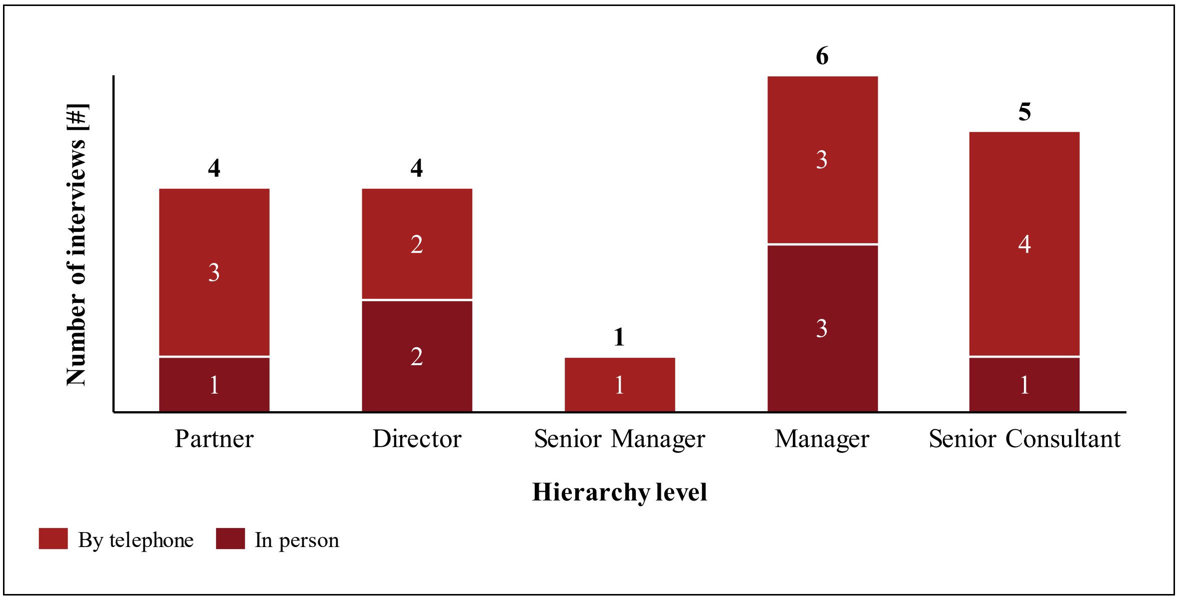
Due to the continuous evolution of data analytics, a cross-sectional design is chosen to ensure comparability and to adequately measure the variability of technology use and adoption (Bryman, 2006). Between March and November 2019, 20 expert interviews were conducted until theoretical saturation was reached. Overall, the homogeneity of the expert group facilitates reaching saturation. Homogeneity is particularly helpful in ascertaining and describing the object of investigation in detail (Schreier, 2010). The distribution of the interview partners by hierarchy level and interview format (in person/by telephone) is shown in Figure 5.1.[91] The sample represents various departments (transaction services: 15; deals analytics CoE: 4; data and analytics consulting: 1) from leading audit firms (Big Four[92]: 19; Next Ten: 1).

[90] Note that interviews with consultants, i.e., the hierarchically lowest ranked employees, are not conducted due to their lower expected expertise. However, their perspective is captured as part of the questionnaire.

[91] A detailed list of interviewed experts is presented in Table A.1 in the appendix.

[92] Interview partners from all Big Four companies are represented.

Figure 5.1: Number of interviews by hierarchy level and interview format



Source: Own illustration

On average, the interviews last 64 minutes. They are audio-recorded (Lamnek and Krell, 2016) and subsequently transcribed "to a smooth, apparently straightforward summary of the main ideas" (Miles, Huberman, and Saldaña, 2014, p. 71) as the analysis focuses on the content explicitly stated by the interviewees (Dresing and Pehl, 2010).[93] The transcripts are analyzed paragraph by paragraph using open coding (Flick, 2009; Strauss and Corbin, 1998). The interview findings concerning the use and adoption of data analytics in FDD are presented in Sections 5.2 and 5.3, respectively.

5.2 Use of data analytics

The expert interviews reveal that the use of analytics covers the entire FDD process; yet, each phase contains different elements of analytics. Hence, the subsequent sections describe and provide examples of the different types of data and analytics used in each process phase as outlined in Section 2.2.4 (Sections 5.2.1 through 5.2.7). Afterwards, the suitability of data analytics, which is already assessed in section 2.2.6, is discussed (Section 5.2.8). Next, the time-related implications of introducing analytics as compared to continuing to use conventional tools are explained in detail (Section 5.2.9). Finally, the use of data analytics is summarized (Section 5.2.10) and an outlook to the future is presented (Section 5.2.11).

[93] For the spectrum of transcription approaches see Höld (2009).

5.2.1 Due diligence preparation

The initial phase of due diligence, the preparation stage, is primarily characterized by the organizational planning of due diligence (e.g., team set-up, time scheduling, coordination with other parts of the M&A process) and the preparation of data for the ensuing analysis phase (see Section 2.2.4.3). In this phase, the focus of analytics use lies on recent developments in data availability and access. Data preparation and its effects on the FDD process are discussed.

5.2.1.1 Trends in data availability and technology development

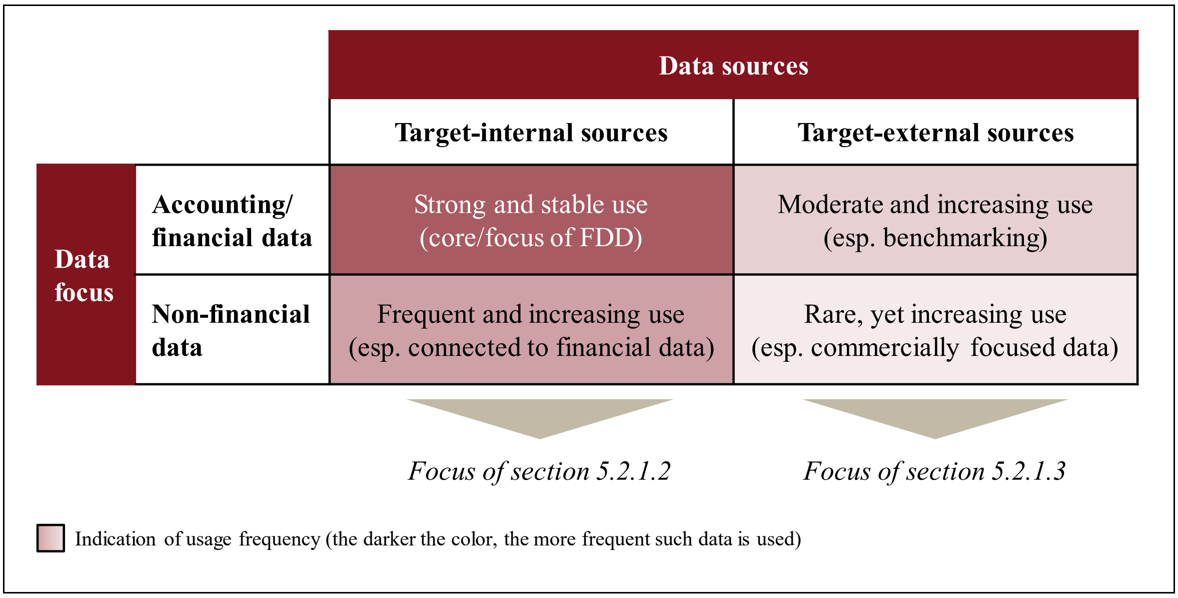
The general developments towards increasing data availability, higher standardization of data formats, greater options for sharing this data, and the technical feasibility to analyze large, complex data sets also apply to due diligence *(P1, D4, M3, SC5)*. For instance, data access is facilitated through the shift from physical to virtual data rooms *(D1)*. While in physical data rooms, documents were manually brought into a digital format to enable the analysis with standard software, virtual data rooms initially make it possible to immediately download data and process it *(D1)*. An additional benefit is that this shift has led to an increasing standardization of data formats, which can be observed through the growing use of easily processable flat file formats *(SC1)*. In the specific context of M&A, the aforementioned recent developments have led to interested investors expecting to receive ever larger amounts of data from the target.[94] Sellers – especially in exclusivity situations – increasingly provide such data for de-risking purposes, i.e., in order not to give the impression of concealing information, which could lead to losing bidders' interests *(P4, D3, D4, M3, M5, SC4, SC5)* or could results in purchase price discounts due to uncertain financial information (Rauner, 2019).[95] Consequently, the amount of information shared during due diligence has increased steadily over time *(P2, D1, M1, M2, SC5)*. In particular, a transition can be observed from a sole concentration on the target's financial information towards an increasing integrating of non-financial data, both from the target and from external sources (see Figure 5.2). The next sections provide an overview of target-

[94] In line with this observation, Hollasch (2013) describes that the expectations of acquiring companies regarding the scope, level of detail, and quality of FDD have increased since the global financial crisis in late 2008.

[95] In multi-bidder auction processes, sellers are less open to sharing large amounts of data. In particular, due to high cash reserves and investment pressure of potential acquirers, they expect a high level of investor interest – largely independent of the amount of information shared *(P4)*.

internal (see Section 5.2.1.2) and target-external data (see Section 5.2.1.3).[96] The inclusion of new data sources and the concurrent increase of data granularity, which is illustrated below, must also be taken into account.

Figure 5.2: Data usage in FDD



Source: Own illustration

5.2.1.2 Target-internal data

For data from the target, two trends can be observed. First, the scope of data provided by the target companies has expanded considerably. For example, the information sources used include not only financial but also non-financial data *(D1)*. In addition, the data provided is often analyzed with a further recourse to history (e.g., last five instead of three years) *(M2)*. Second, this data is becoming increasingly granular and allow for breakdowns to the most detailed levels *(P2, D1, D3, M1, M2, SC1, SC2, SC3, SC5)*.

While early FDD projects have mainly relied on high-level, aggregated information such as audit reports and management accounts[97], the information has become more detailed over time *(D1)*. For instance, access to monthly trial balances[98] has become a common practice *(D1)*. Moreover, an increasing number of due diligences have

[96] Distinguishing between internal and external information sources is established in prior literature (e.g., Störk and Hummitzsch, 2017).

[97] Management accounts are a set of summarized accounting data (i.e., balance sheet, cash flow, and income statement) prepared for and presented to a firm's management in regular periods (usually every month, fortnight, or week).

[98] Trial balances are accounting reports that list the balances in each of the general ledger accounts.

access to data not only from the target's financial systems but also non-financial data from additional IT systems *(P2, P3, D1, D3, M5, SC1, SC3, SC5)*.

In addition to the expansion of the analyzed data towards including increased amounts of non-financial data, there is a second major development: the granularity of the data has increased massively. Granularity has escalated in two dimensions: (i) time-related and (ii) content-related. First, (i) time-related data is less aggregated. For instance, much information is provided on a daily or monthly level instead of on a quarterly or yearly level *(D3, SC4)*. Requirements towards time-related data granularity must be examined in light of the analysis to be conducted. For the analysis of different accounts, a cornerstone of FDD, the access to monthly account data compared to daily posting data is usually sufficient *(P3, SC5)*. However, daily data is better suited to the analysis of transaction data (e.g., customer, product, or volume data) *(P3)*. Second, (ii) content-related data is also less aggregated. For instance, today's due diligence often makes use of information on a stock keeping unit (SKU) or product level instead of a product group level *(D3, M3, SC4)*. Such a breakdown at SKU level allows the analysis of the product portfolio to take into account different sizes, prices, and volumes than would otherwise have been identified *(P3, M3)*.[99]

Having outlined the developments towards greater data access, availability, and granularity, their determining factors are then derived from the expert discussions. The five essential factors are: (i) the initiator (sell-side vs. buy-side), (ii) the negotiation situation, (iii) the target company size, (iv) the target company's structure, and (v) the industry in which the target operates.

Concerning the (i) initiator, data availability and granularity are much higher in VDD projects than in buy-side engagements *(P1, P4, D1, D3, M2, M5, M6, SC4, SC5)*. In particular, sell-side due diligences are characterized by better access to IT systems *(D1, M1, SC1)* (see also Rauner, 2019) and thus to raw data *(M1, SC3)*, higher data quality *(SC1)*, more time available to analyze the data *(P1, D1, SC3)*, the absence of information asymmetry *(P1)*, and a greater target company interest in executing sophisticated analyses *(M3)*. These more sophisticated analyses may even be used beyond the pure deal scope, such as for controlling purposes *(M3)*. The improved access

[99] Further examples how more detailed data support the various analyses of an FDD as provided in Section 5.2.3 et seqq.

to increasing amounts of data on sell-side due diligence projects triggers a new challenge: building hypotheses concerning the target firm's value drivers. At an early stage, the information requirements need to be defined in order to subsequently validate these hypotheses with granular data using a bottom-up approach *(P1)*. The concentration on value drivers at an early juncture requires better-than-ever industry know-how to initially get access to the right data *(P1)*.[100] In contrast, access to granular data remains more restrictive in buy-side due diligence projects. Target firms are careful to share sensitive data – especially with strategic investors such as competitors – in order to avoid negative consequences if the planned transaction is cancelled or an alternative bidder is selected *(P3, D4, M6)*. In addition, most buy-side due diligences that follow a prior vendor assistance or VDD usually concentrate on targeted analyses that typically do not require large amounts of data *(P2, SM1)*. Because the data shared with the potential buyers is less suitable for using analytics (both content-wise and concerning the format) *(M1)*, the benefits of using such tools compared to traditional approaches are more limited for buy-side than for sell-side clients *(P2, SM1, M6)*.

Over time, data access has become less limited and pure reliance on data selected by the target's M&A advisor has decreased *(P2, M1)* – depending on the (ii) negotiation situation. As the negotiations get more serious (and exclusive), the pressure from potential buyers increases as they seek more detailed information as a bottom-up proof of their value hypotheses *(P1, P2)*.[101] A similar observation is made regarding exclusivity agreements. In exclusivity situations, access to data, information, and management resources is significantly better than in structured auction processes *(P1, P3, D3, M5, SC4, SC5)*.

The third determinant of data availability is the (iii) target company size. Experts report that data availability is generally worse for smaller firms *(P3, M1, M3, SC1)*, which is in line with previous literature (see Section 2.2.6). Besides the arguments listed in Section 2.2.6, a potential cause includes the less advanced data and analytics know-how in the target's finance department *(P3, D4)*. An exception to this general observation are small German enterprises that are able to share their data on a posting-level via a DATEV application programming interface (API) *(M1, SC1)*.

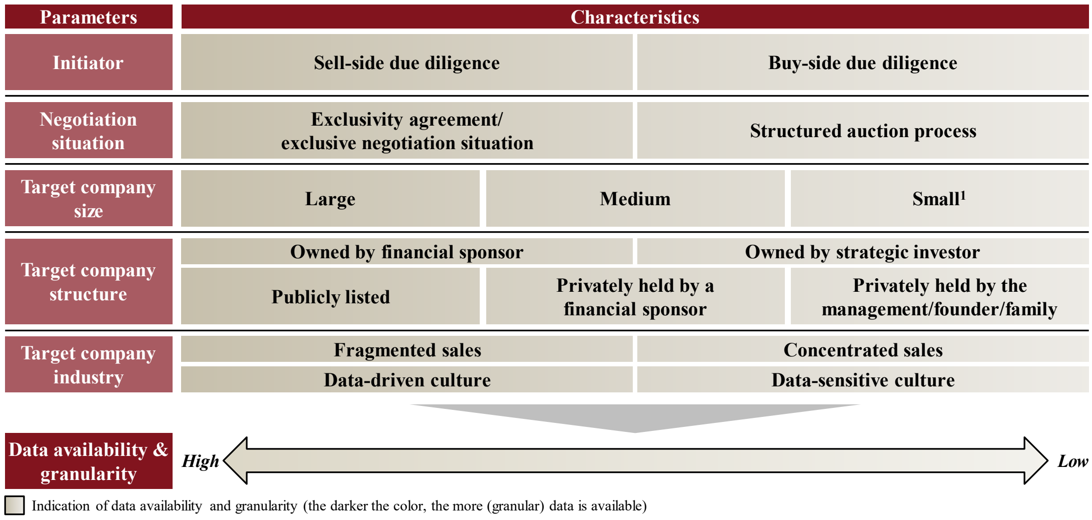
[100] The stronger focus on value components is further discussed in Section 5.2.10.

[101] In line with this view of the interview partners, Andreas and Beisel (2017) state that the provision of information increases as the M&A process progresses.

The fourth determinant is the (iv) target company structure. Publicly listed target firms tend to have comparatively good data availability since they are legally obligated to regularly publicize financial reporting information *(M3, SC5)*. In contrast, privately held companies constitute a bilateral case. Those companies in which financial investors hold a majority stake are often characterized by well-structured performance reporting and steering, which requires good data availability *(M3, SC5)*. Conversely, companies held by their management, founder, or the founding family regularly exhibit poor data availability *(M3, SC5)*. However, the interviewees stress that these are only tendencies and large differences still exist within the groups outlined above.

The fifth and final determinant is the (v) target company industry. The structures of different branches determine the suitability of the generated data for later analysis. For instance, retail players are characterized by fragmented product and customer portfolios with many distribution channels. These circumstances provide a large spectrum of data for diverse analyses *(P2, M3, SC5)*. In contrast, industries with players that offer only a small range of SKUs to a few large clients (e.g., automotive suppliers) are less well-suited to creating sufficiently detailed data for sophisticated analyses *(M3)*. In addition to its structure, an industry's conservatism may foster sensitive data handling (e.g., defense) *(P2)*. The findings concerning the five determinants of data availability and granularity are summarized in Figure 5.3.

Figure 5.3: Determinants of data availability and granularity



Notes:

1) Small German enterprises that can transmit their financial information on a posting-level via the DATEV API constitute a special case with high availability and granularity of (financial) data.

Source: Own illustration

The integration of a broader and deeper data set by the target has not only a positive influence on the core phase of due diligence, the analysis (see Section 5.2.3 et seqq.), but also on (i) information requests and (ii) data preparation. First, it leads to a reduction of (i) information requests *(P1, M1, M2)* and an increasing degree of sophistication in the questions posed to the target management *(M1)*. While the physical client contact has already been reduced through the extensive use of virtual data rooms *(SC1)*, the further improved data access has also reduced inquiries via e-mail or telephone *(P1, M1)*. The remaining requests, in turn, have become much more detailed and specific *(M1, M2, SC4)*. Consequently, the involvement of management resources has been lowered *(D4, M2)*. Smaller targets benefit most from this development, as they tend to devote more management resources to responding to data requests and questions *(M2)*. In addition to saving management resources within the scope of due diligence, the reduction of inquiries also leads to a higher process speed *(M1)*.

Beyond leading to a decrease in requests, the focus of (ii) data preparation has shifted as a result of integrating broader and deeper data sets. In the past, a central component of due diligence preparation was verifying the completeness of the data provided so that all data could be used in subsequent analyses. Today, however, due to time constraints, it is no longer possible to use the large amounts of data provided for analysis purposes. Thus, in addition to checking for completeness, the selection of the right data for later analyses and the verification of data quality are becoming more important *(M2)*. As a consequence of more careful data selection and more specific data requests, the consultants' industry expertise has become increasingly relevant. Additionally, management must be involved at an earlier stage than in the past to support the identification of the right data (from the large amounts of data available) that is decisive for subsequent analyses *(M2)*.

The last paragraphs describe the trends towards increasing data access, availability, and granularity, its determinants, and its consequences for the preparatory phase of due diligence. This paragraph will conclude the section on target-internal data by presenting the most frequently used areas of data. First, it should be noted that the majority of data used is big in terms of volume (from the consultants' perspective), but not big in all dimensions, i.e., it does not have high velocity (no real-time data) and, apart from a few exceptions, has no high variety (mostly structured data)[102] *(P2, D3, M6)*. While information provided by the target company was traditionally limited to the finance and accounting domain, nowadays, more and more non-financial data (e.g., from internal reporting) is included. Primary data categories include product data *(P2, SC3)*, customer *(P2, M5, SC3)* and customer behavior data *(D3)*, store data *(P1, P2, M3)*, country data *(P1, P2, M3)*, and supplier and customer contract data *(M3, M5, SC3)*, which all primarily make it possible to conduct deeper analyses of revenue and profitability drivers. In addition, operative data *(P1)*, product data *(P2, SC3)*, and personnel data *(M3)* provide deeper insights into the cost structure.[103] The examples demonstrate that non-financial data is not used in isolation, but predominantly in conjunction with financial data *(P2, SC5)*. This observed trend towards increasing integration of non-financial data from different IT systems and linkage with financial data is expected to continue going forward *(P2)*.

[102] For the characteristic-based classification of big data, refer to Section 3.2.1.1.

[103] When the target is held by a financial sponsor (e.g., a private equity firm), the same non-financial data from the owner's comparable portfolio companies may be included for benchmarking purposes *(M2)*.

5.2.1.3 Target-external data

In addition to the previously discussed information from the target's IT systems, external data from (i) benchmarking databases *(P2, P3, D1, M2, SC3)* and (ii) other external sources *(D1, SC3)* are used with increased frequency in due diligence. In contrast to the already established use of benchmarking data, the integration of other external, mostly non-financial data (e.g., social media data, geolocational data) is rare *(M2, SC5)*. While some respondents have never experienced the inclusion of external data *(M1, SC1, SC2)*, others estimate that this data is used in approximately every tenth due diligence *(D1, D3, M2, M4)*. The integration of external information depends on two factors. First, the scope of an FDD project; external data is likely used in FDDs that incorporate aspects of a commercial or operational DD, either because these disciplines are not performed separately or because FDD has a broadly defined scope *(M4, SC1)*. In contrast, a standard FDD scope does not transcend the analysis of the target company *(M3)*. Second, the availability of specialized resources that have the technical capabilities to conduct analyses with external, mostly big data. In particular, related analyses often have an ad hoc and non-standard character, requiring programming skills that most consultants currently lack *(SC3)*.

For (i) benchmarking purposes, service providers access public *(M2, M4)* or externally acquired databases *(P2)*. In addition, they are increasingly trying to build up internal databases *(M2)*. The Big Four firms have already developed benchmarking databases for specific, clearly defined purposes (e.g., real estate valuations *(SC3)*, healthcare metrics *(P2, SC3)*, HR metrics *(P2)*, working capital *(P2)*). However, only a few of these companies have already established a comprehensive internal database using financial and non-financial information obtained through previous due diligence engagements *(P2, M2, M4)*. In particular, audit firms are confronted with legal and regulatory restrictions under the WPO. They are also confronted with contractual limitations on the use of anonymized customer data *(P2, P4, D1, M4, SC3)*, which is accompanied by client confidentiality concerns *(P2)*. In addition, the development of such a database requires a high degree of coordination effort and global scaling *(P2, P4)*, which are particularly difficult due to the lack of cross-project comparability (e.g., due to different accounting standards) *(D1)*. Such global benchmarking solutions, though yet established, are already planned by the Big Four companies and will further promote the inclusion of external data in the due diligence process *(P2)*.

In addition to benchmarking data, (ii) other external sources of information are also integrated into due diligence projects. Unlike financial data, the analyses to be conducted and thus the inclusion of external, non-financial data strongly depend on the industry and the transaction *(P3, SC3)*. The most common data types include geolocational and geospatial, demographic, website, social media, transactional, and sensor data (see Table 5.1).

A comparison of the external sources selectively considered in FDD with the big data sources used in other finance and accounting domains (see Sections 3.3.3.1 through 3.3.3.7) reveals large intersections of semi-structured data types, but no intersections of unstructured data types (e.g., audio, image, and video data). More structured data can be analyzed more simply and requires less time exposure. In due diligence projects, which are typically characterized by tight timelines, unstructured data has thus far not been analyzed. Moreover, external data in FDD primarily serves to investigate commercial aspects and has a strong focus on revenue and profitability. In particular, "the majority of firms use big data to analyze the target firm's customers and markets" (Fanning and Drogt, 2014, p. 32). This focus is reasonable due to the high importance of EBITDA in the frequently, at least supplementally, used relative and direct accrual-based valuation methods (Imam, Barker, and Clubb, 2008; Petitt and Ferris, 2013). These commercially-oriented data types serve the two purposes outlined in Section 3.3.3.8: to provide information on items that are difficult to quantify with traditional accounting approaches and to improve the measurement accuracy. In contrast to the revenue and profitability side, data to validate asset and liability valuations (see Sections 3.3.3.4 through 3.3.3.6) is commonly not part of FDD. Instead, due diligence teams rely on the valuations from the audited financial statements *(D1)*.

Table 5.1: Classification of external data sources in FDD

Data type	Sources (examples)	Data (examples)	Interview evidence
Geolocational/geospatial data	• Satellite navigation data (e.g., GPS) • Cartography/map data (e.g., Google Maps)	• Locations and postal codes (e.g., of companies, stores, customers) • Route information • Walking/driving distance and time for different transport connections	P3, D1, D3, M3, M5, SC5
Demographic data	• Federal Office of Statistics • Eurostat	• Population, population density • Demographic development, age structure • Average income distribution	D1, M3
Web data	• Competitor websites • Review websites • Web shops	• Product/service portfolio and prices across competitors • Product/service reviews of target and competitor products (e.g., star ratings, comments) • Product/service presentations in web shops/catalogues	D1, D3, SC3
Social media data	• Facebook • Instagram • Twitter • LinkedIn	• Commentary data (product mentions, conversations between customers about specific products, posts/tweets about products, hashtags) • Action data (likes, shares, retweets) • Emotional expressions (emoticons, emojis) • User profile data (location, age, gender, number of followers) • News and web log mentions	D1, D3, M3, M6, SC3, SC5
Transactional data	• Various web portals	• Spot market/commodity prices • Foreign exchange rates	D3
Sensor data	• Various web portals	• Weather data	D1, D3, SC3, SC5

Source: Own illustration

Since the spectrum of information used encompasses various sources and manifold data types, a diligent selection of the most crucial information for the upcoming analyses is required. Due to time restrictions, it is not possible to cover the entire bandwidth of available data *(D1)*. Moreover, because of their external nature, the selected data must be carefully scrutinized for its veracity. For instance, working with social media data requires an evaluation of the poster's representativeness *(D1)*. It should also be noted that some of the data listed in Table 5.1 can only be extracted with a sufficient experience with and knowledge of advanced tools. For example, while product reviews can be simply compared using ratings, comparisons based on user comments requires technologically advanced techniques, such as natural language processing (NLP) *(D3)*. Extracting of website information, which involves the programming of web scraping solutions, also necessitates increased technical requirements *(SC3)*.

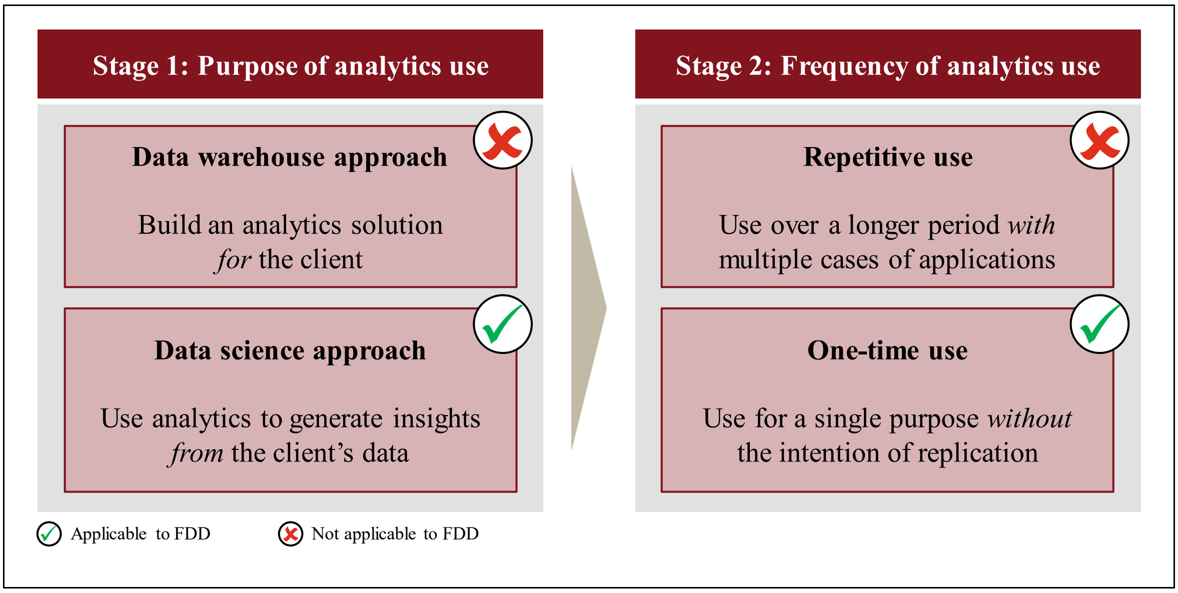
Overall, besides the increasing inclusion of more (and more granular) target-internal data, a shift towards a broadened scope of FDD (paired with the analysis of target-external data) can also be observed *(M3)*. However, such external data mostly serves as either supplemental evidence *(D1)* or for plausibility checks *(M2, SC5)*. Section 5.2.3 et seqq. outline the most prominent examples of how the data presented in Table 5.1 is used in the analysis stage of the FDD process.

5.2.1.4 Data preparation and development of a data model

The availability of a sufficiently large data basis is essential to realizing the advantages of analytics over conventional tools, particularly Microsoft Excel. As explained in the previous sections, the ever increasing availability of data necessitates the more frequent use of analytics solutions. In this regard, data preparation in the context of due diligence preparation is consequently becoming increasingly important. For this reason, the following paragraphs describe the use of data management and analytics tools for cleansing and transforming data and for constructing a data model as the basis for the subsequent analysis phase.

First, it is necessary to understand the different ways that service providers such as audit firms can use analytics and which case meets the criteria of FDD. From the service providers' lens, the purpose and frequency can be distinguished (see Figure 5.4) *(D2)*. FDD is characterized by a data science rather than a DWH approach; it aims to generate insights from the target's data *(D2)*. Moreover, due to the one-off nature of corporate transactions, the analytics usage in an FDD project represents a one-time application *(D2)*.

Figure 5.4: Analytics usage options of service providers



Source: Own illustration

Using a one-off data science approach, analytics in FDD currently exclusively focuses on historical and YTD data. This data is well-suited to the backward-directed use of descriptive analytics *(M1, M2, SC2)*. In contrast to planned data as per the business plan, this data is available on a more granular level *(M1, M2, SC1, SC2, SC3)*. While historical data is commonly available on either an accounts or posting level, most business plans are projected on an account group level *(M1, SC2)*.[104] Moreover, historical and YTD data has a consistent structure across the annual circle (e.g., the same accounts system), while business plan data is commonly less standardized *(SC2)*.

Once analytics is used in FDD, a data model is established that serves as the foundation for the various analyses.[105] The first steps to building such a data model are the extraction, transformation, and loading of the data (see Section 3.1.1.2) *(SC5)*. In most due diligence projects, excerpts from the systems are provided by the target's management *(D1, D4, M2, SC3)* (see also Rauner, 2019), especially for quantitative data *(D4)*. As an alternative, in some deals, the VDD teams *(D1, SC3)* have direct access and can extract data from their client's ERP system accounting and finance

[104] As an exception, the budget year is commonly planned on a more granular level than the following periods of the business plan *(P1)* (see also Bredy and Strack, 2011).

[105] Note that specific analyses that do not need to combine data from multiple sources and across different mapping hierarchies do not require developing a data model. For such analyses, analytics software is mainly used for data cleansing. This observation is especially true for buy-side projects, which are characterized by lower data availability and more specific reviews *(M6)*.

module *(P3, D1, M4, SC1, SC3)* (see also Beckmann et al., 2019). VDD teams can also extract data from other modules or separate IT systems (e.g., controlling, customer relationship management (CRM), HR, production planning) *(P2, P3, D3, M4, SC5)* via APIs or back-up files. However, system access is usually limited to a single data extraction, which means that all relevant data must be extracted at the beginning of the due diligence process *(M4)*. If direct access is granted, consultants are better able to extract data from standard IT systems than for self-developed systems. This is due to the reduced complexity and higher standardization inherent to standard IT systems *(P3)*. Although the extraction step, especially in standard IT systems, is increasingly automated *(D1)*, the extraction of system data still requires the use of specialist teams to program the API *(D1, M4)* (see also Rauner, 2019). A special case exists for small German enterprises whose financial transaction data is available from their tax advisors by transmission via the DATEV API *(M1, SC1, SC2)*. While there is a trend towards direct data access in VDD, buy-side engagements still largely rely on documents provided in the data room *(D1)*. Importantly, prior to using the data from multiple systems, the quality needs to be ensured through a reconciliation with the officially reported data *(P3)*.[106] Therefore, audit firms are already considering the introduction of automated consistency checks of the data processed and the introduction of the analysis of deviations across different data sources *(SC3)*.

Once the data has been extracted, it needs to be transformed, i.e., converted into a standard format and structure. First, files in different formats are converted into an easily processable flat file format (e.g., csv), which is a plain text format that consists of a single data set *(SC1)*. Subsequently, the flat file data must be adjusted using simple operations such as renaming columns, changing the order of columns, or filtering and sorting the data in order to develop a standardized structure across different files. In some audit firms, these standards are even aligned globally *(SC1, SC2, SC4)*. These operations are typically carried out with the Alteryx Designer software *(P3, D1, D4, M1, M2, M6, SC3, SC4)* that uses workflows to process the input data in a predetermined logic *(SC1, SC5)*. Alternatively, some firms use macros coded in Microsoft Excel's programming language Visual Basic for Applications (VBA) (*SC5*). Developing and coding the workflows or macros is particularly time consuming

[106] With regard to the auditing domain, Harder (2018) emphasizes not only the necessity of verifying data consistency when there are multiple sources, but also verifying the completeness, correctness, and reliability of the data.

(SC1). As a result, audit firms have already created standard workflows. These workflows, however, still require input data-specific adjustments for each new due diligence *(SC1)*. The transformation from source data into a predefined output data structure is very difficult to automate *(SC3)*. The actual degree of standardization, and thereby automation, depends on the source of input data. This input data can stem from multiple source systems (e.g., by SAP, Oracle, Infor, Sage, proALPHA, or LucaNet) with different peculiarities due to in-house modifications *(M5)*. When prevailing IT systems (e.g., by SAP or Oracle) with the same basic structure across companies are used, following predefined workflows becomes easier *(SC3)*.

After the predefined data structures are created, a mapping file is built. It includes the relationships between different data and is often implemented using the Microsoft Excel add-ins PowerQuery/Get & Transform *(D1, M1, M2, SC1, SC3, SC4)* and PowerPivot *(D1, M1, SC3)* or VBA-based macros *(M2)*. For instance, cost centers are mapped to different legal entities or subsidiaries are mapped to their parent companies *(M2)*. Moreover, the account hierarchy must be adequately reflected. The mapping serves to properly aggregate the input data. Compared to traditional approaches in due diligence, mapping makes it possible to perform normalizations and pro-forma adjustments only once, while their effects on the different earnings, balance sheet, and cash flow positions update automatically *(SC1)* (see also Rauner, 2019). Moreover, it allows for simple adjustments to account hierarchies (e.g., in order to align differences and allow for comparability between the target's and the potential buyer's account systems) *(SC1)*.

A data model that encompasses all data relevant for the subsequent analyses is developed through extraction and transformation (including the mapping). Instead of working with multiple input sources, as it would be the case without analytics tools, the data model builds a single source of truth *(D1, M6)* – or, technically correctly expressed, a single version of the truth. If all analyses use the integrated data stock, contradictions in the subsequent analyses can be avoided.

In summary, it can be concluded that data extraction, cleansing, transformation, and mapping are still mostly manual efforts *(P3)*. However, these steps are the foundation to later realizing the benefits of analytics in the data analysis, which relies on a standardized data model. Moreover, the manual effort to develop workflows or codes for data transformation only has to be performed once as these elements can be (i) used for all source files and (ii) reused for updates. Such updates can occur either when new YTD or CYT data is available (e.g., trading updates) *(SC1, SC2)* or when historical data is received at a later time *(M4)* (see also Rauner, 2019). Since such historical and current data follows the same structure and formatting, updates can easily be loaded into the data model *(M2, SC1)*.

The Big Four firms' CoE teams are striving to reduce the manual effort of the various data management activities as much as possible. For example, one interviewee reports that endeavors are underway to partially automate the data preparation of core financial data *(SC3)*.

5.2.2 Data model-based use of analytics in the analysis phase

After the data model has been created in the preparatory phase, the various investigations take place in the analysis phase of FDD. Before each area of analysis is explored in detail (see Section 5.2.3 et seqq.), general remarks applicable to all four areas of analysis are made on the automation of data analysis (Section 5.2.2.1) and on the different analytics techniques used (Section 5.2.2.2).

5.2.2.1 Automation of data analysis

As a starting point for the analyses, the data model is converted into the so-called deal tool, which is based primarily on Microsoft Excel software *(SC1)*. While data collection, preparation, and processing take place in a data management tool, the actual analyses may be conducted via Microsoft Excel (Rauner, 2019). Relying on one comprehensive data source with a central mapping file, instead of a multitude of input sources, allows for a very flexible view of the underlying data *(SC1)*. For instance, a P&L can easily be built for a cross-section of countries or legal entities, can be sliced along currencies, countries, or subsidiaries, and can be compared across different time periods (month vs. year) and reporting styles (normalized vs. reported data) *(M1)*.

A current market trend towards using a data model approach *(D1)* that makes it possible to partially automate some analyses *(SC2, SC4)* is evident among the Big Four firms. According to the interviewees, different analyses can be classified into three categories according to their degree of automation and standardization: (i) standardized, (ii) semi-standardized or hybrid, and (iii) flexible analyses.

In (i) standardized analyses, the relevant data from the comprehensive data model is transferred into a predefined input format *(D3, D4)*. Afterwards, the analyses are conducted automatically via predefined workflows that result in a standardized output *(D3)*. While all standardized analyses rely on a predefined input data structure, the exact process of the analyses differs between the audit firms. Some companies rely on self-developed workflows in the off-the-shelf software Alteryx Designer *(SC3)* and others have developed their own technical solutions (e.g., custom-build structured query language (SQL)-based web tools) *(D4)*. Both methods for conducting analyses commonly refer to data from the P&L, balance sheet *(SC3)*, or invoices *(D4)*. Examples of standardized analyses include price-volume analysis *(D1, M3, SC4)* (see also Rauner, 2019), constant currency analysis *(M3, SC4)*, raw material pass-through analysis *(M3)*, store analysis *(M3)*, cohort analysis *(M3)*, and white spot analysis *(M3)*. Since a high degree of standardization is often related to lower attention to specifics *(M4)*, audit firms are currently trying to make their standard analyses more industry-specific *(P2)*.

The second type, (ii) semi-standardized or hybrid analyses, follow the same logic as standardized analyses. The analyses require the prior configuration of certain parameters such as the granularity level of customer data or product data *(D3)*. Finally, the output of both standardized and semi-standardized analyses can be further customized (e.g., by adding filters or breakdowns) *(D4)*.

Unlike the previous two types of analyses, (iii) flexible analyses require manual effort *(P3, D3)*. This type includes analyses that require either little effort or are difficult to implement in the data management software (Rauner, 2019). Moreover, flexible analyses are often target-specific or rely on data with a less predefined structure, which makes it difficult to predetermine a standardized input format *(D3)*. In such cases, additional data transformation and mapping is required. However, experts assume that many of the flexible analyses can also achieve a higher degree of automation *(D3, SC3)*.

In addition, the adaptation of the analysis models is intended to be designed in a more user-friendly fashion *(SC3)*. It should be noted that the leading audit firms have attained different degrees of standardization. While some players have developed globally aligned data models, other players need to adjust their data models considerably on a case-by-case basis *(P4)*.

5.2.2.2 Overview of analytics techniques

The analysis techniques used after the development of the data model are briefly outlined below. The descriptions refer to all areas of analysis before specific explanations for each area are provided in Section 5.2.3 et seqq.

Visualization tools are being used with increasing frequency in FDD to illustrate the results of the three above-described types of analysis or to detect suspicious patterns or outliers in the data. The most common visualization tools employed in due diligence include Microsoft PowerBI *(P3, D1, D4, M1, M2, M5, M6, SC3, SC4)*, the Microsoft Excel add-in Smart *(M1)*, TIBCO Spotfire *(M6)*, and Tableau *(P3, M5, M6, SC4)*. Tableau is the most advanced solution and therefore still requires the involvement of specialists *(D1, M2, M4, SC3)*.

Of the analyses conducted in the course of FDD, the vast majority are descriptive in nature *(D1, D4, M1, M2, SC3)*. The techniques applied include analysis of changes and deviations *(M2)*, pattern recognition *(M1)*, trend analysis *(M1)*, identification of seasonality *(M2)*, and detection of outliers and anomalies *(M1)* – e.g., via visualization *(M1)* or correlation analysis *(M2)*.[107] Overall, two potential use cases derived from adjacent literature are applied in FDD, namely the increasing automation of standard analyses and the use of data mining and visualization techniques to detect previously unknown data patterns (see Section 3.3.4.2). A third proposal, the use of analytics techniques to derive hypotheses about risks and value drivers in early stages in order to subsequently conduct the right in-depth analyses, is not applied. The time-consuming data model development, which also takes place in the early phase of FDD, contradicts this practice. Instead, such hypotheses continue to rely on the target company's existing know-how and the industry in which it operates.

The few predictive analyses (and internal test cases) that deal with forecasts are no longer purely based on historical data and a growth rate. This contrasts with former projections. Instead, they are based on machine learning algorithms with models that

[107] Beyond descriptive analytics techniques carried out by the consulting teams, specialized expert teams apply further algorithms in complex analyses *(SC3)*. For example, specialists use the following algorithms (many of which go beyond the traditional scope of an FDD): recognition of dependencies (e.g., raw material cost pass-through analysis) via linear regression and time-series models, customer analysis via survival analysis, text classification via logistic regression and support vector machines, and pattern recognition (e.g., allocation of account flows to either the parent or standalone company in a carve-out situation) via decision trees *(SC3)*.

are enriched by (i) supplemental factors and (ii) more granular data to increase predictive power *(D1)*. In the medium-to-long-term, they could serve as enhanced plausibility checks for the business plan (see Section 5.2.6) *(M2)*. At present, however, the extensive use of predictive analytics is not feasible due to limitations in the knowledge and skills of target companies, investors, and consultants *(M2)*. However, it is evident that the fourth suggestion derived from adjacent literature, the use of predictive analytics to develop an alternative business plan (see Section 3.3.4.2), will become relevant to FDD in the foreseeable future.

The interview partners could only report from one internal test case involving the application of prescriptive analytics: a churn analysis that identifies which customers would be likely to leave and makes recommendations regarding which customers could be contacted to avoid churn *(M2, SC3)*. However, this analysis would be more appropriately put to use in the post-deal phase to leverage synergy potential when choosing between different courses of action *(D1)*. No current or planned use cases are known for FDD.

Thus, the current focus in FDD still lies in descriptive analytics and increasing the efficiency in data preparation. This is in line with prior results from two due diligence-related research papers and further scientific literature in the finance and accounting domain (see Section 3.3.4). A few interviewees envision a shift in focus towards using predictive analytics *(P2, M2)*. As described in the previous paragraphs and summarized in Table 5.2, three of the four potential use cases developed in Section 3.3.4.2 are either already applied in practice or are likely to be employed in the future.

Table 5.2: Applicability of use cases from adjacent literature in FDD

Suggested use cases from adjacent literature	Applicability in FDD
Model-building techniques to develop expectations (e.g., hypotheses concerning value drivers to support the equity story) in the preparation phase, which are validated with additional data during the analysis phase	**Not applied:** Although it is increasingly important to prioritize the right focus areas for a later review in order to customize data requests accordingly, the short lead time before the start of an FDD project (compared to the regular audit) forces consultants to rely on their industry know-how instead of on a quantitative model.
Automation of (primarily descriptive) **standard analyses**	**Applied:** In line with existing due diligence literature (Beckmann et al., 2019; Rauner, 2019), standardized and semi-standardized/hybrid analyses are largely automated.
Clustering and (interactive) visualization to identify previously unknown data patterns such as anomalies and outliers	**Applied:** Data mining and visualization techniques are applied to analyze changes and deviations, recognize patterns, analyze trends, identify seasonality, or detect outliers and anomalies across a broad range of different areas of analysis. However, it must be borne in mind that the detection of anomalies is a regulatory activity in auditing, whereas in FDD it is only relevant in certain instances.
Predictive analytics techniques to **verify management assumptions** concerning the prospective development of the target or to potentially create an independent, **alternative business plan** that builds on prior analyses of the historical situation	**Potentially applied in the future:** Internal test cases conducted by FDD service providers reveal that the forecasting of an independently developed business plan, based on machine learning algorithms with models that are enriched by (i) supplemental factors and (ii) more granular data to increase predictive power, could become a reality in the foreseeable future. In the medium-to-long-term, these forecasts could serve as enhanced plausibility checks for the business plan. However, the extensive use of predictive analytics is not feasible at present due to limitations in the knowledge and skills of target companies, investors, and consultants.

Source: Own illustration

The following four sections deal with the use of analytics in the individual areas of analysis.

5.2.3 Profitability analysis

The profitability analysis represents the main field of use in those FDD projects in which analytics is applied *(D1, D4, M1, SC1, SC5)*. First, (i) using analytics tools provides direct benefits to the profitability analysis, such as increased efficiency and transparency. The different analyses of the revenue and cost situation particularly benefit from the (ii) increased granularity of target-internal data, which allow for a better root cause analysis than when more aggregated data is used, and the (iii) supplemental use of target-external data sources.

The direct advantages provided by (i) analytics solutions are delineated using three examples. First, reconciliations that involve complex group structures (e.g., multiple legal entities operating across numerous countries) are improved through analytics usage *(P1, M1)*. Building up on a single data model instead of a plethora – often hundreds – of input files, these reconciliations can be conducted more efficiently and more transparently than with traditional deal tools *(P1, M1)* (see also Rauner, 2019). Moreover, analytics makes it possible to flexibly create connections between data. This feature is particularly useful in carve-out transactions, where the deal scope has yet to be defined (Rauner, 2019). For example, an interview partner reports that analytics was used to derive a complex sum of the parts P&L in a carve-out deal *(M3)*. In this buy-side project, separated income statements for approximately 300 franchise stores were prepared and segmented into clusters. The flexible assignment of store clusters by criteria such as country, store size, ownership, and profitability facilitated compiling the stores to be purchased as a bundle for the investor *(M3)*. The use of analytics also allows for new insights (e.g., through drill-downs), and thereby more detailed discussions between the target and the acquirer *(M3)*. Another example that benefits from the capabilities of analytics tools to analyze large amounts of data is the calculation of currency exchange effects, i.e., the translation *(P1, SC4)* and transaction effects *(P3)*. In particular, the constant currency analysis to determine the translation effect benefits from the simple analysis of complex settings (e.g., in the context of numerous legal entities in different currency zones) *(P1, SC4)*. In addition, all transactions must be valued at the closing rates in order to accurately determine the transaction effect. This requires the analysis of vast amounts of data, which can only be performed efficiently with the help of analytics software *(P3)*. In some cases, the analyses of currency effects are combined with external data. Foreign exchange rates are automatically downloaded from the web and integrated into the analysis *(SC4)*. Beyond these two examples, analytics enables the processing of large data sets at the account or even transaction level. The analysis and visualization techniques of modern analytics software facilitate the identification of non-recurring and non-operating income and expenses *(M3)*.

The profitability analyses benefit from than just the efficiency and transparency increases resulting from the use of analytics software. Thus, the following paragraph presents selected analyses that particularly benefit from the availability of (ii) more granular target-internal data that can be examined using analytics solutions. The prime example is the price-volume analysis *(P1, P3, D1, M2, M3, M5, SC1, SC4, SC5)* (see also Rauner, 2019). Using granular data (e.g., on a product or SKU level instead of a product group level) allows for the application of a bottom-up approach to calculating price, volume, and mixed effects. This granular data enables the resolution of the mixed effect. This granular data also makes it possible to assign previously non-assignable revenue changes to new product launches, phase-ins of new

SKUs, and phase-outs of obsolete SKUs. The effects can also be broken down along dimensions other than products (e.g., customers/customer segments, stores, geographies). In addition to price-volume analysis, customer churn analysis, which is particularly important for target companies with a large customer base and recurring sales (Pomp, 2015), benefits from granular data *(D1, M2)*. Sufficiently granular data makes it possible to use predictive analytics in order to forecast customer churn, i.e., the attrition rate of the customer base (Pomp, 2015), based on the regression of historical data *(M2)*. The interconnection of FDD and CDD also benefits from the improved data situation. The churn rate analysis often forms the basis for further investigations within the scope of the CDD (Pomp, 2015). Moreover, two further commercially oriented analyses, the customer lifetime value analysis *(D1)* and cohort analysis *(D1, M5)*, are also enhanced by the availability of more granular data and the deeper insights it allows. However, due to their strong commercial focus, they are only selectively part of FDD.[108]

Going beyond those top-line analyses, more granular target-internal data also enhances cost-oriented analyses in FDD. For instance, material cost analyses *(D1)*, such as the raw material cost pass-through analysis *(P3, D3)*, benefit from the inclusion of raw material prices from the bills of material and from the supplier contracts' pass-through clauses *(SC3)*. This data makes it possible to estimate the risk of price fluctuations on the basis of historical developments and external market data *(D3)*. This external market data is especially relevant to the price fluctuations of commodity products. For instance, the lead time between when the raw material price is set and actual pass-through to the end customers, as well as the actual pass-through share (at the estimated lead time), can be determined with linear regression models *(D3)*. However, not all cost positions are well-suited for the use of analytics software. In particular, limitations exist in areas where data can only be drawn from poorly maintained IT systems but not from either the ERP system or management reports. This condition often applies to IT systems that contain data relevant to analyzing personnel costs *(M2)*. However, when personnel data is available, analyses of the FTE development, FTE per function, employee age, length of employment by the company, employee salary components, and the like can be carried out at a more detailed level than in the past *(M3)*.

[108] As outlined in Section 2.2.4.4, the scope for commercial analyses in FDD depends on FDD's connection to CDD and on whether a separate CDD is carried out.

Table 5.3 presents an overview of those analyses whose quality improved through the integration of more granular data from the target and the application of analytics solutions.

Table 5.3: Data analytics in the profitability analysis – Use cases with target-internal data

Analysis	Benefits	Interview evidence
Reconciliations	• Handling of complex group structures (e.g., multiple legal entities operating across various countries) through mapping logic • Increased efficiency, transparency, and traceability through use of a single data model instead of a plethora of input files	P1, M1
Sum of the parts P&L	• Flexible connection of data from income statements of different units of analysis (e.g., stores)	M3
Constant currency analysis (translation effect)	• Accurate and efficient determination of the translation effect in complex settings (e.g., in the context of numerous legal entities in different currency zones)	P1, SC4
Identification of non-recurring and non-operating income and expenses	• Analysis and visualization of vast amounts of account or transaction-level data to identify outliers and anomalies	M3
Analysis of the transaction effect	• Handling vast amounts of transaction-level data (e.g., for numerous legal entities over the course of three to five years)	P3
Price-volume analysis	• Resolving previously non-assignable revenue changes (mixed effect) and breaking them down into new product launches, phase-ins of new SKUs, and phase-outs of obsolete SKUs based on the integration of very granular data (e.g., on a product or SKU level instead of a product group level) • Break-down of price, volume, and mixed effect along dimensions other than products (e.g., customers/customer segments, stores, geographies)	P1, P3, D1, M2, M3, M5, SC1, SC4, SC5
Customer churn analysis	• Precise forecasts of the attrition rate of the customer base based on the regression of historical data (predictive analytics)	D1, M2
Customer lifetime value analysis	• Increased sophistication in the prediction of customer lifetime value through more precise information on the anticipated attrition rate (see customer churn analysis) and the use of predictive analytics techniques instead of heuristic techniques	D1
Cohort analysis	• More nuanced segmentation of customers into subsets based on larger information on their shared characteristics from the target's CRM system	D1, M5
Raw material cost pass-through analysis	• Determination of price fluctuation risks based on information from bills of material and from supplier contracts • Enrichment with external market price data	P3, D1, D3, SC3

Source: Own illustration

Compared to other review areas within FDD, profitability analysis benefits most from the increased availability and granularity of the financial and non-financial information from the target companies. Moreover, it also derives the greatest value from the analysis of (iii) supplemental, target-external data compared to other areas of review *(M2, SC1, SC5)*. Such external information is most prominently used in commercial or operational due diligences *(SC4)*. However, they also play an increasing role in FDD in transactions where either the financial and other forms of due diligence are linked or where these forms are included in the scope of FDD.

In most instances, analyses of revenues or profitability drivers with a high degree of detail use external data sources and combine them with target-internal information. Thus, external data is primarily used to gain supplemental evidence *(D1)* or for plausibility checks *(SC5)*. Since the spectrum of external data for supplemental analyses is merely infinite, this paragraph presents the most important use cases highlighted by the experts. The most frequently used data types comprise (i) geolocational and geospatial, (ii) demographic, (iii) website, (iv) social media, (v) transactional, and (vi) sensor data (see Table 5.1). The following examples briefly describe the analyses that are most prevalent along each of the six data types. A prominent use case of (i) geolocational and geospatial data in due diligence is the white spot analysis. It links the locations of stores or branches with data on potential customers within a defined catchment area (e.g., a certain driving distance) in order to discover previously untapped market potential, the so-called white spots *(D1, SC3)*. In addition, the white spot analysis can be enriched with (ii) demographic data (e.g., density of population, distribution of income, age distribution) in order to further increase its significance *(P3, D1)*. Customer behavior and product usage data can be derived from the (iii) target's website and external websites. This data can ultimately be used to analyze their impact on revenues *(D3, SC1)*. Technical experts also apply web scraping to extract product and pricing information from the target's and its competitors' websites or e-commerce shops for benchmarking purposes *(D1, D3, M3, SC3)*. These product portfolio benchmarks can be supplemented by product reviews from websites (e.g., star ratings from comparison portals) *(D3)*. Customer perception is captured using social listening techniques; most prominently used is sentiment analysis of (iv) social media data, which can subsequently be linked to revenue development *(D1, D3, M3, SC3)*. Using text recognition algorithms and word classification dictionaries, social media commentary and action data is categorized into different sentiments (typically positive and negative). Such analyses, however, can only classify single words or phrases but cannot take into account the contexts in which these terms are used. While such context-related analyses are becoming increasingly precise with the help of NLP algorithms, their practical use lags behind *(SC3)*. Raw material pass-through analysis is conducted using (v) transactional data, such as raw material prices from supplier agreements or spot markets *(D3, M3, SC3)*. Finally, (vi) sensor data in the form of weather data is integrated into the analysis of historical revenues to identify and adjust for seasonal patterns *(D1, D3)*. Table 5.4 provides a summary of the use cases with target-external data, some of which have been outlined in this paragraph.

Table 5.4: Data analytics in the profitability analysis – Use cases with target-external data

Analysis	Interview evidence
Geolocational/geospatial data	
White spot analysis to identify growth opportunities	D1, SC3
Location benchmarking across competitors based on economic activity	D3
Analysis of revenues by customer locations/residences	SC2
Transport cost optimization (e.g., route optimization, fleet optimization)	M3, SC3
Validation of internal flows of goods and cash between different locations and customers	SC5
Demographic data	
Analysis of customer population around locations (e.g., stores)	P3, M3
Website data	
Analysis of customer behavior (linked to revenue analysis)	D3, SC1
Analysis of product usage (linked to revenue analysis)	D3, SC1
Benchmarking with competitors' product portfolio and prices	D1, D3, M3, SC3
Social media data	
Analysis of customer behavior (linked to revenue analysis)	D3, SC1
Analysis of product usage (linked to revenue analysis)	D3, SC1
Analysis of customer sentiment/satisfaction (linked to revenue analysis)	D1, D3, M3, SC3
Evaluation of target employees' using profile data (e.g., LinkedIn-based capability analysis)	D3
Transactional data	
Analysis of raw material price and production cost development	SC3
Raw material pass-through analysis	D3, M3
Sensor data	
Analysis of weather-related effects in historical revenue development	D1
Adjustment of seasonality based on weather data	D3

Source: Own illustration

5.2.4 Balance sheet analysis

Analytics is less often used for analyzing the balance sheet than the profitability situation for two primary reasons. First, many transactions follow the cash and debt free premise and use EBIT or EBITDA multiples to determine the target's value. The focus thus lies on the profitability analysis, which includes deriving the pro-forma, normalized earnings *(SC1)*. Second, the balance sheet, rather than the P&L, contains potential distortions through intercompany transactions leading to a lower data quality *(SC1)*.

Nevertheless, analytics is regularly leveraged in the balance sheet analysis. The applications emphasized in the expert discussions are presented here. First, the use of analytics tools allows for the processing of larger amounts of data. This makes it possible to examine a longer history of data that reaches beyond the traditionally scrutinized previous three fiscal years *(M2)*. Analytics thereby supports more precise determination of necessary adjustments to the opening balance of the balance sheet item at hand *(M2)*. In addition to the analysis of longer periods, analytics is also used to more efficiently allocate positions to net debt, working capital, or fixed assets *(SC4)* and to build the balance sheet in the net assets format (Rauner, 2019). With its mapping logic, this approach allows balance sheet items to be assigned to the three categories only once and not separately within each spreadsheet in which the element appears, as would usually be the case with cell reference-based Microsoft Excel software *(SC4)*. For the same reason, analytics carries forward the P&L effects from the quality of earnings analysis that have an impact on the balance sheet and, inversely, also considers balance sheet adjustments that have an earnings effects in the adjusted P&L *(SC4)*.[109] This consideration is necessary in order to avoid a simultaneous reduction in EBITDA and the formation of a corresponding balance sheet item as net debt. Such a situation would erroneously result in a double deduction in the derivation of the equity value (Pomp, 2015). Lastly, analytics software and its visualization features are used to detect anomalies in balance sheet items *(SC4)*. The most common field of application is working capital *(SC4)*. For instance, visualizing the age structure of receivables and payables based on an outstanding items list allows for the better identification of anomalies *(M1, M3)*.

In the future, experts expect techniques such as machine learning to identify outliers that require normalizations and adjustments. They also anticipate automated suggestions for the classification of balance sheet items into net debt, working capital, or fixed assets *(P2)*. However, interviewees expect that the machine learning-based suggestions will still require subsequent expert judgement through review of the audit reports and discussions with management *(P2, D3)*. This need for professional judgement resembles the use of analytics in forensics *(P2)* and parts of the auditing process (Gepp et al., 2018).

As described in the previous paragraph, irrespective of the data analyzed, analytics software already yields substantial advantages in the context of balance sheet analysis. However, in contrast to profitability analysis, both non-financial target-internal

[109] For the reciprocal effects between normalizations and pro forma adjustments of earnings and balance sheet items, refer to Pomp (2015).

and target-external data is rarely analyzed *(SC4)*. The audit opinion is adhered to for balance sheet items; therefore, non-financial data is almost exclusively used to analyze balance sheet item development that has taken place since the last audited financial statements *(M2)*. For example, currency exchange rates garnered from external sources are examined to reflect the impact of fluctuations on various balance sheet items *(M2)*. Only in rare exceptions is the audit opinion questioned, such as in the following prominent examples outlined in the expert interviews: the validation of the inventory valuation *(M2, M3)* and the corroboration of the provisions for slow-moving or obsolete inventory (SLOB) *(M3)*. In these cases, geolocational data and SKU prices facilitate determining the actual values of inventories and their proportion of SLOB. This can subsequently be compared to assumption-based valuations in order to adjust the balance sheet accordingly and in order to reflect value differences in the target's valuation *(M3)*.

5.2.5 Cash flow analysis

Analytics software is rarely used in the cash flow analysis *(M1, M2, M3, SC1)* for three main reasons. First, as outlined in the previous section, the vast majority of in particular, smaller transactions use earnings multiples or accruals-based valuation techniques instead of the cash flow-based approaches to determine the target's value *(SC1)*. Thus, the focus of these deals is on profitability analysis. Second, the FCF is typically determined using the indirect approach, which is based on earnings positions and balance sheet item value differences that have both already been examined in previous steps *(M1, M3, SC1, SC4)*. Third, especially small targets lack data on a cash flow basis *(SC1)* (see also Brauner and Neufang, 2011; Bredy and Strack, 2011) – especially in continental Europe (Bredy and Strack, 2011).

As outlined, the FCF is mostly derived using the indirect approach *(M1, M3, SC1, SC4)*, though analytics is used to carry those changes made in the P&L and balance sheet forward to the determination of the cash flow *(SC4)*. A few further use cases for analytics arise if data on a cash accounting level is available. For instance, the FDD team may use analytics to perform a liquidity analysis based on daily cash flow data *(M2, M3)*. Such an analysis is of particular relevance in restructuring cases because cash planning is accomplished on a per day basis *(M3)*. Moreover, the very granular data on a transactional level reveals anomalies over the course of a month. Cash and cash equivalents, as well as intercompany liabilities, can be monitored to uncover abuse of financial discretion between the monthly opening accounts and closing accounts *(M3)*.

5.2.6 Business plan validation

Traditionally, the validation of business plan calculations has come from scrutinizing the management's assumptions and premises based on historical developments *(D1, M3)*. In the future, the business plan could be challenged using predictive analytics. In internal test cases, the Big Four firms have already prototyped own forecasts using advanced analytics techniques such as machine learning algorithms *(D1, D3)*. In these tests, historical monthly account-level data was used but the algorithms did not outperform the traditional analyses of the business plan *(D3)*. At first glance, these results appear surprising since typical business plan analyses often lack a sophisticated approach (e.g., simple updates of historical figures using estimated growth rates) *(P2)*. However, experts expect that machine learning-based models could deliver better forecasts when using very granular information (e.g., SKU instead of product level data) enriched by supplemental, external factors and benchmarking data. This more detailed data is expected to increase predictive power *(P2, D1, D3, M3)*. Some audit firms are already investigating the use of predictive analytics for the purpose of business plan validation *(P2, D3)*. This option would allow audit firms to provide an alternative self-developed business plan that, besides comparing management reporting with a worst, base, and best case, could be included into scenario analysis *(P2, SC3)*.

In contrast to the analysis of historical and YTD information, however, data from the business plan itself is not analyzed with the help of analytics tools. In comparison to historical and current information, the business plan, with the exception of the often granularly planned budget year, contains highly aggregated data *(P1)* (see also Bredy and Strack, 2011). In addition, the structure of business plans differs widely within and between companies *(SC2)*. Therefore, using analytics tools that would require establishing a new data model presents no advantages over the commonly used Microsoft Excel software when analyzing planned financial reports *(SC2)*.

5.2.7 Due diligence reporting

The most discussed topic regarding the application of analytics for due diligence reporting purposes is the creation of interactive dashboards using Tableau or PowerBI *(P1, P3, SM1, M3, SC1, SC4, SC5)*. Such forms of visualization facilitate management discussions *(D4, M3)*. Moreover, the experts interviewed regard such dashboard solutions as an expedient supplement to the formal documentation (especially the final report) during due diligence but do not consider it an appropriate substitution *(P1, P3, SM1, M3, SC1, SC4, SC5)* (see also Beckmann et al., 2019).

The experts report on the use (or the planned use) of visualization techniques to facilitate the interaction with their clients (both targets and investors) in the exchange of interim results *(D4, M3)*. For example, such solutions enable quick and easy testing of value hypotheses during the development of the equity story or make it possible to answer ad hoc questions that arise in discussions *(D4)*.

This form of dynamic visualization could also be used to share data room content and the analyses performed during the sell-side due diligence with the buy-side teams *(P1, SM1, SC4, SC5)*. Unlike the deal tools currently available (see Sections 5.2.1.4 and 5.2.2), which only provide a snapshot, dashboards provide a flexible view of the underlying data *(SC4)*. Sharing such dashboards between the sell-side and buy-side necessarily increases transparency *(D4)*. However, the selling party has various motives not to share the underlying data used in the dashboard solutions. A key motive is the fear of losing control over the data. Target firms have concerns that the buy-side could perform analyses for which they are not prepared *(D3, D4, M2, SC4)*. Other motives to restrict the sharing of the underlying data include liability concerns *(P3)* and time constraints imposed by the target-internally required legal approval of shared data *(SC4)*. For this reason, FDD service providers are currently developing server-based dashboard solutions that allow various analyses to be performed without granting access to the underlying data *(P1, P3, SM1, M3, SC4)*. Some experts expect that an increasing use of analytics by the target companies will reduce these concerns and lead to complete data sharing in the distant future *(SM1)*. Another challenge for service providers is the static nature of due diligence report. Not only targets and investors, but also banks and insurance companies involved in the transaction traditionally rely on the formal due diligence report because of its clearly defined scope and its static condition. Thus, experts note that the introduction of interactive dashboards must be accompanied by the ability to freeze the status of the final report for download in order to satisfy risk management and liability requirements *(P2, D4)*.

Despite the limitations on data sharing and the need to create a frozen status, most service providers do not only use dashboard solutions for discussions with the management, but also have an eye to the future by performing test cases with long-standing clients to establish dashboards as a complement the final FDD report *(P2)*.

Nonetheless, some experts have concerns about setting up dashboards supplementary to the final FDD report. First, they argue about its relevance. Put differently, they emphasize that formal documentation should be limited to the concise conclusions and results of essential analyses conducted by the service providers. This view is well illustrated by the following quote:

> 'We get paid for one view, not for twenty potential views.' [1:14:26] *(D3)*

The report should provide a balanced view and not leave open questions for management to answer or overload clients with too much information *(P1, D3)*. A second concern pertains to the consequences of a (too) positive perception of dashboard solutions. Specifically, one respondent fears that an overly positive perception of such solutions could lead to commoditization and increased competition from technology companies with the ability to create dashboards more quickly and more cost-effectively *(D3)*.

Despite these two concerns, the overall impression from the expert discussions is that the establishment of dashboard solutions for management discussions and as a formal deliverable supplementing the final FDD report is merely a question of time.

The automated generation of tables that are used in the FDD report is another topic besides visualization; however, it is discussed less. For example, one interviewee discusses current considerations regarding the automated integration of tables, charts, and graphs from the analytics tools into the final report *(SC3)*. Accordingly, Rauner (2019) writes that "[f]irst approaches for a direct adoption are already apparent, so that it is a question of time until the direct linking of the analysis results of the database with the reporting template becomes the norm" [translated from German] (p. 935).

5.2.8 Suitability of data analytics – Review of the critical assessment

In Section 2.2.6, it was posited that the integration of more granular financial and also non-financial data, paired with the use of analytics, could support FDD in fulfilling its ultimate three objectives: (i) identification and consideration of risks as well as protection from risks, (ii) identification of value potentials, and (iii) negotiation and decision-making support (see Section 2.2.4.1). This view is fully supported by the expert interviews. While the first two objectives primarily benefit from greater insights into the target, the latter is reinforced by an increase in efficiency. Importantly, service providers currently concentrate their analytics efforts on enhancing process efficiency. In particular, they intend to overcome a newly emerging cost-benefit trade-off related to the application of analytics tools indicated in Section 2.2.6 and presented in detail in the next section (see Section 5.2.9) *(P3, D1, D3, D4, M3, M4, M5, SC1, SC2, SC3, SC4)*. After the first audit firms have reached a necessary level of analytics utilization, they are slowly shifting their focus from increasing process efficiency to gaining more insight from the various data sources that complement financial data *(P2, P3, D1, D4, M3, M4, SC1, SC4)*. The following quotes reflect this observation:

> 'It is all about standardization and automation of processes in our context – right now at least.' [14:52] *(D4)*

> 'The use of data analytics today is more efficiency-oriented and should be more value-oriented in the future.' [translated from German] [52:37] *(SC1)*

Concerning the first two objectives, the experts highlight increasing transparency and reduced information asymmetry between the seller and potential acquirers *(D1)* (see also Beckmann et al., 2019; Rauner, 2019). On the one hand, the use of analytics software in due diligence allows for the analysis of larger amounts of data that form the basis to generate deeper insights *(SC1)*. On the other hand, the increasing recourse to more granular (also non-financial) data from various target-internal and target-external sources provides insights into previously unexploited areas, especially in profitability analysis. Moreover, the analysis of larger, more granular, and more diverse sets of data has become less prone to error through the use of a comprehensive data model *(D1, M1, M3)*. For example, avoiding versioning problems caused by different reference files enhances the data quality and leads to more reliable, quantitatively sound results *(D1)*. The increased accuracy also strengthens the solidity of the equity bridge in the context of valuation *(M3)*. In addition, analytics techniques themselves, i.e., decoupled from the data used, allow for new insights on the target. The slicing and dicing logic enables analysts to quickly create new views of the data and enables them to break it down by legal entity, country, segments, and so forth *(P3, M3, SC1)*. Combined with the flexible mapping logic, it makes it possible to generate new compilations of the target assets for sale (e.g., creation of new financial statements of the carve-out scope on an accounts level) *(M3)*. The use of analytics thereby supports both objectives of FDD: discovering financial risks and identifying value potential.

As previously outlined, the current focus of using analytics lies on the processual improvements that support the third objective of FDD. In particular, the use of analytics leads to efficiency gains driven by an increasing degree of standardization and automation of the analyses, updates, and deliverables based on the data model logic *(D1, D4, M1, SC2, SC3)*. Increasingly standardized data formats allow for automation in the data preparation since this phase still requires mostly manual efforts *(SC2)*. In addition, offshoring to shared service centers (SSCs) in low-cost countries also enhances process efficiency *(P3, SC2)*. The higher speed of both routine *(P3, D1, M1, M3)* and ad hoc analyses *(M1, SC1)*, as well as updates, is of particular importance in M&A because of the short deal cycles *(D4)*. The largest time-based improvements result from updates that can be conducted in a few hours instead of a few weeks due to the reusability of workflows *(P3, SC1)*.

The time savings also allow for greater customization and more detailed interpretation of the analyses performed *(D4, SC4)*. For example, management discussions, management's preparation for negotiations, and management's decision-making can be enhanced with the appealing visualizations and an interactive presentation of data *(P3, SC1)*. Furthermore, the scope of due diligence may be expanded and additional analyses may carried out in areas of particular interest to management *(D3)*.

Finally, the data cube as the single version of the truth that is available to all project members facilitates collaboration across the different parties involved in the transaction *(D1)*.

Overall, the processual improvements through analytics lead to faster decision-making based on more objective discussions that rely on extensive, quantified information stemming from a comprehensive data pool *(D1)*.

To sum up, as described at the beginning of this section, audit firms are in their infancy of analytics use. They are currently concentrating on raising their levels of adoption and on becoming more efficient. This will allow firms to establish the basis for the generation of new insights in the future. While audit firms are already gaining additional insights from the analysis of larger, more granular, and more diverse data sets, they plan to shift their priorities to expanding this insight-oriented view once critical adoption and efficiency thresholds are reached. The following quote underscores these considerations:

> ‘We are still harvesting the efficiency-driven benefits, but the question that arises when you have those efficiency benefits: What do you do with your time? […] You need to drill deeper […] and as our use of analytics becomes more mature, the scope [of due diligence] will widen and include more and more data sources and different types of analysis.’ [15:33] *(D4)*

It must be noted that this development does not rely purely on the efforts of audit firms but also relies on the companies involved in the transaction. These companies have a substantial influence on data availability and further contextual factors that are key to using analytics (see Section 5.2.1.4).

Although the use of analytics largely supports all three of FDD’s objectives and audit firms are striving to increase process efficiency, there are two major drawbacks: Time-intensive manual effort is required for data management activities and it is not feasible to share interim results at early stages. Consequently, a trade-off arises as to whether the numerous advantages outweigh these disadvantages. This conflict is presented in detail in the subsequent section.

5.2.9 Emerging cost-benefit trade-off of analytics use

The use of analytics software leads to incisive changes in the due diligence process as compared to the sole use of the conventional spreadsheet program Microsoft Excel. On the one hand, analytics leads to significant time savings in the preparation phase (e.g., through reduced, more specific data requests) and especially the analysis phase of due diligence (e.g., through the rapid integration of updates, partially standardized and automated analyses, and the rapid response to ad hoc requests for specific analyses). In addition, Rauner (2019) indicates that the use of analytics software provides synergies for future deals, especially in carve-out transactions where the implemented group structure is transferred into a mapping logic. On the other hand, preparing the data and developing the data model takes longer. More specifically, data extraction, transformation, mapping, and loading still require time-consuming manual efforts and thus, lead to a longer lead time than traditional approaches *(M1, M2, SC1, SC2)*. During the time needed to set up the data model, interim results for parts of the deal scope (e.g., prioritized legal entities or countries) cannot be shared *(M1, SC2)*. However, these steps are essential to realizing the previously outlined benefits of analytics.

While the use of analytics solutions is indispensable to some FDD projects due to the sheer volume of data *(P2, D2, M2)*, other projects do not have enough data available for meaningful use *(D3)*.[110] The majority of FDD projects, however, fall between these two extremes. In these cases, careful consideration of a newly developed cost-benefit trade-off is essential. It is necessary to question whether the upfront investment of time for data preparation can be offset by the subsequent savings of time (or justified by other benefits).

Therefore, it is important to understand which determinants affect this trade-off, besides data availability (see Figure 5.3). In the expert interviews, nine determinants could be identified. These determinants are assigned to three categories: (i) deal-related and target related factors, (ii) project-related factors, and (iii) data-related factors.

Concerning (i) deal-related and target-related parameters, multiple experts observe that divestures, i.e., the sale of parts of a business (e.g., in a carve-out), a stronger drivers for complexity than the sale of an entire target company *(P2, D3, M1, SC5)*. Divestures of (parts of) a business require making precise distinctions regarding the target's remaining business. Thus, modeling of such transactions is more intricate and can be enhanced with analytics software (e.g., by utilizing a simple distinction to categorize items between the business for sale and the remaining business). Another determinant is the deal scope *(P2, P3, D3, M6)*. The larger the number of legal entities, countries, products, suppliers, and customers involved in the transaction, the

[110] Two similar extremes are described by Harder (2018) for the auditing domain. He expects the use of data analytics and conventional approaches to coexist in the foreseeable future. On the one hand, some clients lack the technical capabilities (e.g., non-existent or incompatible ERP and booking systems), which necessitates the use of traditional approaches. On the other hand, some areas of the audit process (e.g., journal entry testing) require the application of data analytics software to cope with the high data volume.

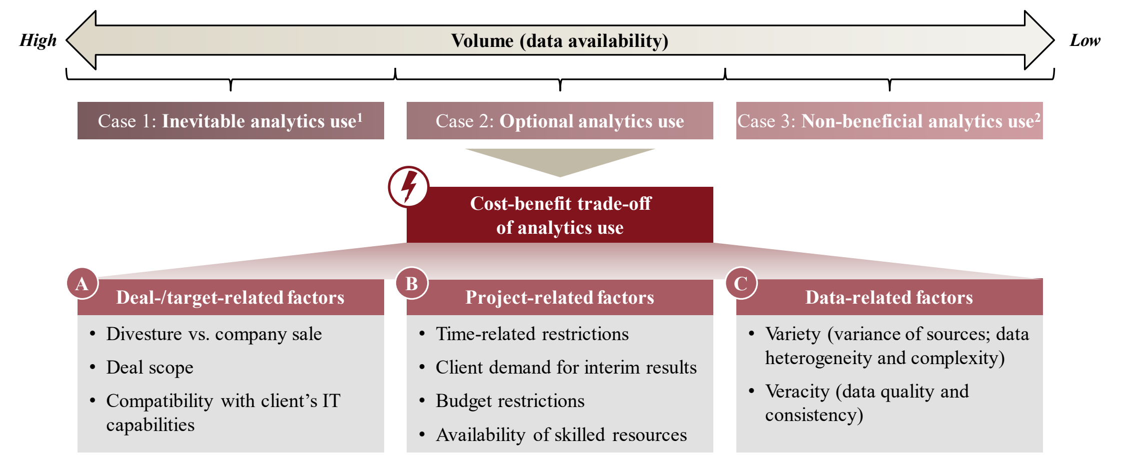
greater the data complexity and hence, the benefits of using analytics *(P2, P3, D3)*. Finally, the client's IT capabilities must not be underestimated *(D1)*. For example, one respondent reported that an investor was using an outdated version of Microsoft Excel that was incompatible with certain formats *(D1)*.

The most frequently mentioned (ii) project-related factor is the time restriction of due diligence *(P2, P3, SM1, M1, M6, SC5)*. A minimum length of time is needed to set up the data model, which is based on the current skill level of the consultants and the degree of automation required. The more time the consultants have time to conduct the analyses, the more likely they are to benefit from the time savings realized through analytics use. FDDs that take longer are more likely to include trading updates of new monthly or quarterly data whose processing is significantly accelerated by analytics. Another factor mentioned by the interviewees, is the clients' demand to obtain immediate interim results *(SM1, M1, SC2)*. For instance, investors may want to discuss first results for key parts of the overall deal scope within the first days of due diligence. The initial analysis of prioritized parts of the deal scope, however, stands in sharp contrast to the data model-centric logic of analytics. Its approach is based on the development of a comprehensive model that contains all relevant data, which can subsequently be analyzed either as a whole or for parts of the deal scope. Evidence from the expert interviews suggests that this conflict has not been sustainably resolved. Instead, some audit firms use separate teams to meet client expectations: one team that works with analytics software over the entire course of FDD and another that conducts the initial analyses to be able to present interim results *(SC2)*. Such a procedure, in turn, depends on a third factor, budget constraints *(P3, SM1, SC5)*. The fourth project-related factor is the availability of personnel that has obtained the knowledge to use analytics in trainings and in prior projects *(P3)*. Thus, most audit firms strive to allocate their team members to projects such that each team possesses people with the required skills *(P3)*.

Finally, two (iii) data-related factors impact the cost-benefit trade-off of using analytics. Going beyond the sheer volume of data (see at the top of Figure 5.5), the variety and veracity are also relevant. In this context, variety includes both the plethora of sources whose data needs to be set into relation to each other and the plurality of data structures *(D2, D3)*. In the setting of due diligence, veracity primarily refers to data quality and consistency *(D2)*.

The decisive factors in the emerging cost-benefit trade-off of analytics usage in FDD projects are summarized in Figure 5.5. In contrast to Rauner (2019), who briefly lists decisive parameters (data availability, initiator, complexity, investor requirements, time plan, competences of the project team), this study provides a more comprehensive and thorough overview of determinants and structures them in a conceptual framework.

Figure 5.5: Determinants of analytics usage in the cost-benefit trade-off



Notes:
1) The use of analytics software is inevitable when the amounts of data to be analyzed exceed processing capability thresholds or lead to significant performance deficits of common spreadsheet tools (esp. Microsoft Excel).
2) The use of analytics software for very small amounts of highly aggregated data leads neither to increased efficiency nor to additional insights as compared to the use of common spreadsheet tools (esp. Microsoft Excel).

Source: Own illustration

5.2.10 Summary

In the past decade, due diligence has been subject to considerable changes. With the shift from physical to virtual data rooms, investors' expectations are constantly growing and sellers, especially in exclusivity situations, are increasingly providing greater amounts of data for de-risking purposes. Accordingly, data access, availability, and granularity (both time-related and content-related) have significantly improved. Besides financial data, target firms often also share non-financial information related to their customers, products, operations, and so forth. This non-financial data is not used in isolation, but predominantly in conjunction with financial data. Their primary advantage is to be able conduct deeper analyses on revenue and profitability drivers, and to provide better insights into the cost structure. The availability of internal data depends on multiple determinants: (i) the initiator (sell-side vs. buy-side), (ii) the negotiation situation, (iii) the target company size, (iv) the target company's structure (public vs. private ownership), and (v) the industry in which the company operates. Moreover, service providers are beginning to integrate big data from target-external sources. Yet, in contrast to the already established use of benchmarking data, the integration of other external, mostly non-financial data is rare (in approximately every tenth due diligence). The most common data types encompass geolocational and geospatial, demographic, website, social media, transactional, and sensor data. These data types are mostly (semi-)structured; they can be analyzed more simply and thus with less time exposure. External data often has an emphasis on commercial aspects. This is due to the high importance of EBITDA in the frequently, at least supplementally, used relative and direct accrual-based valuation methods (Imam et al., 2008; Petitt and Ferris, 2013).

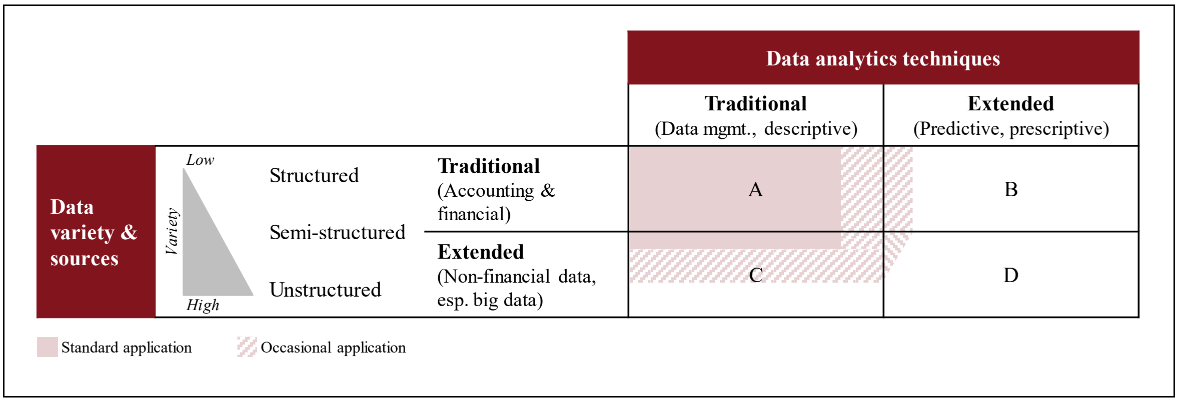
Consequently, the analysis of larger, more granular, and more diverse data sets from the target, but partially also external sources, triggers the use of analytics software. The greater reliance on large, multi-facetted data sets leads to notable changes when paired with the opportunities that analytics tools provide. In the *preparation phase* of the FDD process, data is partially exchanged through the provision of direct access to the targets' IT systems – especially in sell-side FDDs. Access to immense amounts of data means that selecting the right data becomes increasingly important. This development leads to fewer, though more detailed information requests and an earlier involvement of management within the process. In particular, smaller companies that tend to have stronger management involvement in responding to data requests and questions benefit from this development. However, the biggest change in the FDD process takes place during data preparation. Building a comprehensive data model in a predefined format and structure requires manual, time-consuming steps such as data extraction, transformation, mapping, and loading. The data model logic implies that intermediate results (e.g., for prioritized parts of the deal scope) can no longer be shared. This approach also leads to an extension of the time required for data preparation. A cost-benefit trade-off emerges for projects that neither necessitate nor prevent the use of analytics due to extremely high or low data availability: (i) Deal-related and target-related factors, (ii) project-related factors, and (iii) data-related factors must be weighed up to determine whether the efficiency-related benefits of analytics (rapid integration of updates, partially standardized and automated analyses, rapid response to ad hoc requests for specific analyses) justify the additional lead time required.

During the *analysis phase*, the *profitability analysis* and, albeit to a lesser extent, the *balance sheet analysis* benefit most from the increasing degree of standardization and automation – as predicted based on FDD-related and adjacent literature (see Section 3.3.4.3). Besides such efficiency enhancements, new insights can be gained through many analyses (especially commercially oriented ones). On the one hand, analytics technology makes it possible to conduct established analyses on a more granular level. Such analyses thereby provide more informative and meaningful results (e.g., price-volume analysis). This advantage is particularly helpful in assessing intangible off-balance sheet assets such as the customer base. On the other hand, the inclusion of non-financial data from both the target and external sources, as well as advanced analytics techniques, makes it possible to perform analyses that were not feasible beforehand (e.g., customer sentiment analysis). In contrast, analytics is employed less often in the *cash flow analysis* due to the use of earnings multiples or accruals-based valuation techniques instead of cash flow-based approaches to determine the target's value, the application of an indirect approach to determine the FCF, and the lack of data, especially for small targets. To date, the *business plan validation* lacks the application of data analytics as most business plans contain highly aggregated data and lack a uniform structure within and between different target firms. However, FDD service providers are currently exploring the use of predictive analytics for the purpose of self-developing an alternative business plan (as suggested in Section 3.3.4.2).

Finally, the *reporting phase* is characterized by first attempts to introduce interactive dashboard solutions in order to facilitate interim discussions with management and in order to provide a valuable supplement to the final report. Audit firms are also considering using automation to create tables and charts for the FDD report.

The overall use of different data sources and analytics techniques described throughout the previous sections is summarized in Figure 5.6 based on the conceptual framework introduced in Section 3.3.2 (see Figure 3.10). The figure illustrates that with the availability of accounting and financial data at transaction level, traditional data sources are used to the greatest possible extent. Conversely, non-financial data is not yet analyzed by default across all FDDs. While target-internal data (e.g., customer or product data) is regularly used, the inclusion of external sources has been rare thus far. Furthermore, it should be noted that a large proportion of the data used is big in volume, but not big in all dimensions. In particular, the often-used target-internal data is neither generated at a high velocity (no real-time data) nor does it vary greatly in its structure (mostly structured data). In the case of analytics techniques, it is evident that the initial focus is on data management and descriptive analytics. Although the use of these two forms is labelled as traditional in the original framework, it can be described as progressive since it differs considerably from the use of conventional software tools. However, the full utilization potential has not yet been realized; in particular, very few analyses already make use of advanced techniques (e.g., customer churn analysis).

Figure 5.6: Big data and data analytics application in FDD



Source: Own illustration

5.2.11 Future outlook

Three trends for the future use of analytics in FDD can already be substantiated today.

First, service providers strive to increase adoption and maximize efficiencies in the near future. They plan to enlarge the spectrum of automated analyses, to consider introducing automated consistency checks of the data prepared *(SC3)* and the automated generation of parts of the final report *(SC3)*, and aim to increase the portion of work that can be handled by offshore resources in SSCs *(P2)*.

Second, audit firms aim to gradually shift from the efficiency-driven perspective towards a more insight-oriented perspective in the medium-to-long-term future. Insight-orientation represents gaining increased knowledge through deeper analysis and more sophisticated techniques. Although the vast majority of analyses are currently descriptive in nature (see Figure 5.6), the proportion of predictive analytics is expected to rise in the future *(P2, D4, M2, SC3)*. One anticipated use case is the preparation of an alternative business plan in order to challenge the management's forecasts. Another anticipated use case, similar to today's use of predictive analytics in fraud detection, is the machine learning-based identification of outliers. These findings would subsequently be combined with expert judgement in the quality of earnings analysis *(P2, D3)*.

Third, the interview partners expect the various data sources, as well as the reliance on a single version of the truth, to lead to stronger links between the different due diligence disciplines *(P1, P2, M6, SC1)*. In particular, the scope of FDD is supposed to extend towards a stronger focus on levers of value accretion (e.g., synergies), the derivation of suggestions for business steering, and the calculation of their financial implications *(P1, P2, P3, M2, SC1)*. As outlined, these changes are enabled by increasing data availability and technological advancements. In addition, investors increasingly demand these topics to be covered as part of an FDD. Client demand can be explained by two drivers. First, the increasing complexity of many business models requires investors (and thus also service providers) to develop a better understanding of value drivers, which in turn entails taking a broader view beyond the traditional scope of FDD *(P2)*. Second, the persistently low interest rate environment, coupled with the high cash reserves of strategic investors and the dry powder of private equity firms, leads to fierce competition for the most attractive assets and thus to rising asset prices (Bain & Company, Inc., 2020; McKinsey & Company, Inc., 2019). Increasing price pressure consequently reinforces the need for investors to identify areas of value appreciation *(P1, P4)*. Thus, the focus of FDD services is not only developing in an insight-oriented direction, but also in a value-oriented one.

In summary, it is predicted that FDD service providers will leverage analytics to drive process efficiency in the short term and shift to a more insight and value-oriented approach in the medium-to-long-term.

These trends and developments lead to three prospective consequences for due diligence service providers.

First, FDD will become more integrated into the M&A process and collaboration with other work streams will increase (e.g., by using a common data pool) *(P2, D1, SC3)*.

In particular, the company valuation work stream is well-suited to integration due to its reliance on the findings of FDD (Pomp, 2015) and the existing use of analytics tools (Mackenstedt et al., 2018). Moreover, Feix (2019) and Feix and Popp (2018) already point to this development with their call for an integrated M&A platform that can be used across all phases of the M&A process. For instance, the increasing focus on value creation in FDD requires a stronger link between the levers identified and corresponding measures in the integration phase.

Second, the skills needed by consultants will change significantly *(P2, M2)*. The growing consideration of value potentials will require greater industry knowledge from consultants *(P2)*. At the same time, the increasing use of not only data management but also advanced analytics requires technical skills (currently contributed by CoEs) that exceed the know-how of the majority of consultants *(M2)*. Overall, the functional knowledge of classical FDD topics, industry knowledge, and advanced analytics capabilities already exceeds the profiles of most consultants. Following this observation, the increased use of mixed teams is likely. In contrast to audit teams that are predicted to consist of both functional and technical staff in the future (e.g., Harder, 2018), the prospect FDD teams are expected to also incorporate industry competences. In line with this projection, the majority of respondents in the study by Merrill Corp. (2018) expects that the number of people involved in the M&A process will increase moderately until 2022 through the use of technology.

Third, the changes to the due diligence process that have already been observed and still expected to come could lead to adaptation of the service providers' business models. It is difficult for FDD service providers to raise their fees in the amount necessary for recouping the investment required to set up the technical, organizational, and personnel infrastructure in a market where time and materials pricing is widely applied *(D3)*. One identified reason is that the final deliverable, the FDD report, has not (yet) noticeably changed. This means that there is no increased willingness from the clients to pay for benefits they neither notice nor perceive *(D3, SC1)*. For this reason, consultancies are currently developing interactive dashboard solutions as a supplement to the FDD report (see Section 5.2.7). In the long term, it is conceivable that elements from subscription models or value-based pricing will be adopted by the firms in order to adapt the traditional bill-by-hour approach to the changed conditions *(P1, D3, SC1, SC3)*.

The aspects outlined above cannot be achieved until analytics has been fully integrated into FDD. For this reason, the next section is devoted to the topic of adoption.

5.3 Adoption of data analytics

In the context of analytics adoption, an initial assessment of the adoption level and the influencing factors is performed on the basis of expert interviews (Section 5.3.1). For the organizational factors, it must be noted that adoption is commonly defined as the decision to adopt or the intention to adopt (Jeyaraj et al., 2006). However, the units of analysis in the qualitative analysis of this thesis, Big Four firms in the German-speaking area (and a few neighboring countries), have already decided to use analytics within FDD. The analysis at the organizational level therefore has a retrospective character (Section 5.3.2). Beyond the organizational analysis, the individual adoption factors are also assessed on the basis of expert interviews before a survey-based determination is carried out (Section 5.3.3). Finally, a brief summary picks up the findings of the qualitative analysis of adoption (Section 5.3.4).

5.3.1 Level of adoption

The experts are asked to estimate the proportion of FDD projects that already use analytics software. Various breakdowns (e.g., by initiator, project size, geography, sophistication of analytics tools) can be made at the discretion of the interviewees, i.e., without reference to established adoption models so as not to influence the results. These breakdowns are intended to provide initial trends of adoption across various classifications.

According to the experts, the use of analytics by audit firms and their transaction services departments in the German-speaking area lies between 30% *(D4, M2)* and 50% *(M1)* with a sharply increasing trend *(D1)*. However, significant differences can be observed for the various breakdowns, which allow for trend statements to be made.

The split by initiator reveals higher adoption rates on sell-side (50% *(P3, M6, SC3)*) than buy-side FDDs (20% *(M6, SC3)*, 30-40% *(P3)*). However, the traditional wisdom that analytics is merely exclusively applied on sell-side projects can be disconfirmed *(D1, D3)*. In particular, analytics is relatively well-adopted in situations with an exclusivity agreement, which are characterized by enhanced access to data as compared to auction processes *(D3)*.

Thus, some organizations started to cluster their due diligence projects according to size instead of the traditional sell-side/buy-side distinction. In particular, they observe considerably higher adoption rates for projects with more than 50,000 EUR of revenue (80% *(D3)*) than for those projects with lower revenues. For the projects with lower revenues, analytics is rarely adopted *(D3)*. In order to foster adoption, one national affiliate of a Big Four firm has introduced a mandatory threshold that obliges due diligence teams to use analytics software for assignments that pass revenues of 150,000 EUR *(D3)*.

The break-down by country reveals that analytics adoption is much higher in the U.S. and Australia (100% *(M2)*) than in the Netherlands (>50% *(D3, M2)*) and in the German-speaking area (between 30% *(D4, M2)* and 50% *(M1)*). These differences result from circumstances that are external to the audit firms as well as organization-internal cross-country distinctions. Experts emphasize the different characteristics of Anglo-American firms and their financial reporting, which have a considerable effect on data availability *(D3, SM1)*. These observations are in line with theoretical considerations: Nobes (2014), referring to Zysman (1983), classifies the U.S. financial system as capital market-based, whereas the German financial system is categorized as credit-based. This distinction stresses the greater disclosure in Anglo-American countries, which is accompanied by higher data availability and a more receptive stance towards sharing data *(SM1)*. In line with this observation, experts report a lower client demand, especially among investors, for the use of analytics in the German-speaking area *(SM1)*. Moreover, interviewees report audit firm-internal differences that result in different cross-country adoption levels. Based on varying levels of client demand, organizations in some countries began testing the use of analytics earlier than others, which has led to different levels of adoption *(M2)*.

Finally, some experts have split the adoption by analytics tools. Adoption of data management and descriptive analytics software varies ranges between 33% *(SM1)* and 55% *(SC1)*. Some interviewees note that the visualization component of these tools is still underutilized. In contrast to simpler solutions, the experts consistently report adoption rates between 0% and 10% for advanced analytics tools *(SM1, M3, SC1, SC2)*. This observation is in line with findings from prior studies in the auditing field that reported higher acceptance for basic features than for advanced features as well as a gradual shift towards the inclusion of analytics (see Section 4.2.1).

Further breakdowns are conceivable, but were not performed by the experts. The tendencies towards adoption derived from expert discussions are summarized in Figure 5.7. It should be noted that these are cross-project trend statements. The necessary prerequisites for the use of analytics at the individual project level are described in Section 5.2.9. Further adoption-promoting and adoption-inhibiting factors are illustrated in the following sections.

Figure 5.7: Determinants of adoption level differences

Parameters	Adoption tendencies				
Initiator	Sell-side due diligence	>	Buy-side due diligence with exclusivity agreement	>	Buy-side due diligence with structured auction process
Deal size/ revenues	Large (Fees: >150,000 Euro)	>	Medium (Fees: 50,000-150,000 Euro)	>	Small (Fees: <50,000 Euro)
Country of adopting organization	Anglo-American regions	>	German-speaking area		
Sophistication of analytics tools	Data management and descriptive analytics	>	Advanced analytics		

Source: Own illustration

5.3.2 Organizational adoption factors

As explained in Section 5.3, the Big Four firms have already responded to the developments of increasing data availability and technology advancements (see Section 5.2.1.1) and have consequently decided to introduce analytics software as part of their due diligence services. Thus, the analysis of the organizations' adoption decisions is a merely retrospective in nature. However, organizational factors still play an important role in the further expansion of the use of analytics. In particular, interviewees view the increase in usage as an essential prerequisite for the further development of their analytics-based due diligence services *(D3)*. The three factors of the TOE framework must therefore be considered in light of both the prior decision to introduce analytics as well as the current status of its use. The following sections are devoted to examining the three cornerstones of the TOE framework: the technological, organizational, and environmental context.

5.3.2.1 Technological context

In the original TOE framework, the technological context contains two components: technology availability and characteristics. In the previous literature review on analytics adoption by audit firms, a third factor, the cost-benefit ratio, was also highlighted.

Technology availability

Commonly, audit firms employ a tool-agnostic approach, i.e., they use interoperable software that best suits the task at hand *(D1)*. To ensure a good task-technology fit, the tools are selected by specialist teams that possess both functional deals know-how and technology know-how *(SC5)*. When choosing technology, the audit firms almost exclusively opt for off-the-shelf tools (see Sections 5.2.1.4 and 5.2.2) *(D4)*.[111] Compared to findings from prior literature in the auditing domain (see Section 4.2.2), the reliance on standard tools is found to be higher in FDD according to the experts interviewed. Thus, due to the great availability, good compatibility with existing IT solutions, and moderate licensing costs of commoditized off-the-shelf tools, analytics technology itself is not a barrier to entry for smaller audit firms *(D4)*. In sum, the positively evaluated availability of analytics technology is not supposed to lead to cross-company differences in adoption. Instead, it fosters adoption across Big Four and Next Ten audit firms *(M5)*.

Technology characteristics

The application of analytics tools can be characterized as a synthetic type of innovation that leads to moderate change (Baker, 2012) because existing technologies are used in a novel context, FDD. The application of analytics has processual implications (e.g., through the data model logic, which is unprecedented in the FDD process). It leads to a different allocation of workload in the preparation and analysis phase, respectively, and raises a cost-benefit trade-off (see Section 5.2.9). In addition, the incorporation of non-financial information by means of analytics technology increases the consideration of compliance and risk management aspects such as data transparency (e.g., location of data storage) and data security (e.g., need for anonymization of person-related data such as creditors, debtors, personnel) *(M1, M2)*. Moreover, the use of analytics compared to traditionally applied software, especially Microsoft Excel, requires building up an enhanced technical skill set. This aspect, however, is evaluated in terms of the organizational context (see Section 5.3.2.2) and the individual effort expectancy (see Section 5.3.3.2). To conclude, the characteristics of analytics as a synthetic type of innovation affect the FDD process. Although none of the experts identified technology characteristics as a driver for firm-level decisions

[111] As an exception, one Big Four firm uses a proprietary web-based platform to analyze invoice data *(D4)*. One Next Ten firm plans to self-develop a tool that incorporates most core analyses of an FDD *(M5)*. Those two companies also rely on standard software in addition to the in-house-developed tools.

to adopt, the audit firms' adaptability to processual changes may play a vital role in the actual use of analytics. In particular, pairing existing expertise with learning effects from early, first mover experiences is considered key to prepare for such changes *(D4)*.

Cost-benefit ratio

Previous literature on the use of analytics in the field of auditing was unclear about whether cost savings from increased process efficiency and offshoring might be offset by decreased revenue resulting from less billable consulting hours (see Section 4.2.2). The expert interviews reveal that this concern does not hold true. Instead, the increased process speed is primarily used to conduct additional, detailed investigations *(P1, D3, SC4)* and the increased efficiency allows audit firms to offer a lower price in competitive situations *(P1, SC3)*. However, it remains unclear whether (or when) the increased efficiency (while maintaining a stable revenue base) will recoup the investments required to set up the technical, organizational, and personnel infrastructure *(D3)*, which are not considered in prior research.

Therefore, in line with theoretical considerations, there is no clear-cut evidence that cost-benefit deliberations have an effect on firms' decisions to adopt.[112]

5.3.2.2 Organizational context

The organizational context as defined in the original TOE framework contains four components: formal and informal linking structures, communication processes, firm size, and resource slack. In addition, prior literature from the auditing discipline highlights a fifth aspect: potential intra-organizational benefits through spillover effects on other services.

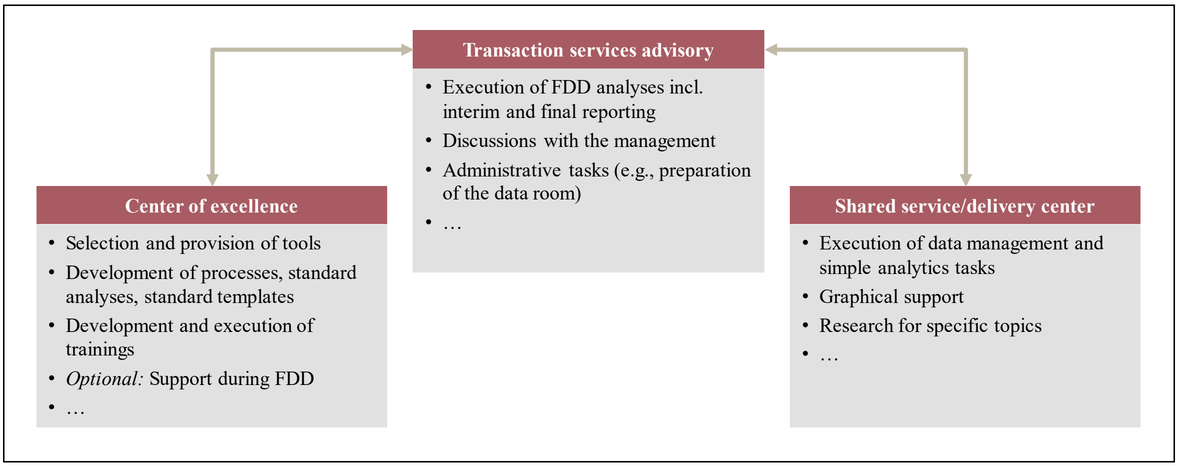
Formal and informal linking structures

To evaluate the linking structures of the Big Four, it is essential to first understand their organizational set-up (see Figure 5.8). The Big Four commonly involve three different units in their transaction services business. The consultants who possess functional expertise conduct due diligence services *(M2, SC5)*. A CoE with specialized technical experts is responsible for the development and maintenance of tools,

[112] The above discussion acknowledges such opportunity costs as the case that a company could lose market share if it did not offer analytics services while its competitors do. For related considerations, refer to the paragraphs on "Industry characteristics and market structure" in Section 5.3.2.3.

methods, workflows, process templates, and training materials *(D2, D4, SC5)*. Although the CoEs typically cover the entire deals-related service offerings from the Big Four, their focus lies on due diligence. In some, but not all, Big Four firms, the CoE also supports due diligence project work for complex analyses that require advanced analytics skills that consultants commonly lack. Moreover, consultants interact with SSCs whose offshore resources primarily support simple, manual parts of the data preparation and analysis in order to benefit from labor cost disparities and time differences *(D2, M1, M2, M6, SC5)*.

Figure 5.8: Organizational set-up of service providers



Source: Own illustration

While the organizational structure is very similar among the Big Four firms, their concrete design differs across and even within these firms. In particular, the degree of centralization of the transaction services advisory units differs across firms and across their respective national affiliates *(D3)*. Theory suggests that decentralized organizational structures are better suited to the initial adoption decision, whereas more mechanistic structures with a centralized decision-making are better suited to the actual implementation (Zaltman et al., 1973). In the context of analytics adoption in FDD, the expert assessments confirm results from prior literature. It can be observed that those Big Four firms with decentral decision-making processes and the involvement of a multitude of partners have been first movers in their decisions to introduce analytics in the field of transaction services *(M1)*. However, the actual adoption across FDD projects is more difficult for decentrally steered firms *(D3)*. In particular, they lack alignment across their national affiliates although the coordination of analytics efforts on a global basis would lead to benefits from economies of scale (e.g., by setting up on the same tools) as well as mutual learning *(P1, D2)*. Moreover, individual rather than collective incentive structures impede investments necessary to foster adoption (e.g., in trainings) *(P3, M3, M5, SC5)*. As a result, one of the Big Four firms uses a hybrid approach, i.e., a combination of local autonomy of the service lines, a central development of tools and concepts, and regional support managers to connect the different stakeholders *(M6)*.

The same considerations hold true for the organizational design of the CoEs *(D3)*. While some firms rely on a global CoE *(D4, SC5)*, others prefer multiple autonomously operating CoEs that coordinate on a supranational level *(P3, D1, M1, M2, M6)*. For the CoEs, the additional question arises whether they should be staffed with either only technical experts (e.g., data scientists) or with mixed teams consisting of both technical and functional experts *(D3)*. The expert interviews reveal that those CoE teams that mainly consist of technical experts have a higher need for agents, which is in line with prior literature (see Section 4.2.2). These employees need to coordinate the collaboration between functionally-focused consultants and their technically-oriented co-workers in order to ensure implementability *(D1, D3)*. Some of the Big Four offer secondments, i.e., temporary assignments, on their CoE teams to strengthen linkages between the CoE and advisory business *(M1, M2, SC5)*. The interviews also reveal that exchanges between the consulting and CoE teams can be facilitated when CoE co-workers are involved in due diligence projects (e.g., for complex analyses that require advanced skills in analytics such as programming) *(P2)* and when trained consultants coach other team members (e.g., analytics champions) *(SC2)*. These exchanges can also facilitate adoption. Therefore, in accordance with theory, the existence of linking structures through different organizational units promotes adoption.

Communication processes

Essential aspects that can inhibit or foster adoption decisions, are top management behaviors and communication processes. According to the expert discussions, the top management across all Big Four firms strongly supports the increasing use of analytics in the M&A process in general and FDD in particular *(P1, SM1, M3)*. Similarly, the firms' partners have a high awareness *(D4, M1, M2, M5)* and their attitude towards analytics usage is characterized as positive and open-minded *(M1, M2)*. Moreover, some firms have realized that existing incentives may undermine the adoption of analytics in individual cases. For example, the partners' traditional revenue-based remuneration components are based on the bill-by-hour pricing approach, which prioritizes short-term revenues from FDD projects over investments (e.g., in trainings) *(P4)*. Hence, consultancies have started to seek a stronger alignment of the firms' and their partnerships' interest in fostering adoption. In contrast to mostly supportive partners, a mixed attitude could be observed among senior managers and directors. Some of them look forward to, or are enthusiastic about, the use of analytics. In contrast, others prefer familiar approaches and view the integration of analytics with restraint skepticism, or even apprehension *(P3, D1, D4, M1, M2, SC1)*. The employees in the latter group have learned the tradition way to perform the analyses during due diligence and, are not sufficiently involved in the operational analyses in order to gain an understanding of data processing with analytics in their current roles *(P2, SC1)*. They have often not yet worked with analytics tools and therefore lack the necessary skills and confidence in analytics *(SM1, M1, M3)*. In addition, the Big Four do not set any financial incentives that would increase the extrinsic motivation to use analytics *(M5, SC2, SC5)*. Moreover, budget pressure, time pressure, and potential unknown factors that are hard to assess due to a lack of experience make it more difficult for senior managers and directors to use analytics in their projects, even with high intrinsic motivation *(SM1, M1, M3, SC2)*. While senior managers and directors do not have a substantial impact on the decisions to adopt analytics made by the firms' leadership, their persuasion is decisive when assessing the analytics use for individual due diligence projects. For this reason, their perceptions are illustrated in detail in the sections that deal with adoption at the individual level.

Firm size

Another critical organizational determinant is firm size. In previous literature, size is predominantly associated with financial resources. As explained in the last section, the analytics tools used in FDD are almost exclusively standard solutions with moderate licensing costs. From the perspective of smaller audit firms, this initially speaks in favor of the decision to adopt analytics solutions. However, it must be emphasized that a considerable part of the standardization and automation of data preparation and analysis steps can only be accomplished through the prior development of clearly defined process steps and workflows. These tasks require back office teams, whose size differs notably between the Big Four and smaller competitors. Building up such teams (e.g., in the form of a CoE) would require large personnel and financial investments *(P1, P3, D3, D4, M5)*. Thus, non-Big Four audit firms without CoEs and SSCs rely on simple, self-developed tools that require less effort and less support *(M5)*.

Moreover, the reduced scope of such in-house-developed tools limits the need for costly trainings *(M5)*. Overall, firm size is an essential driver of analytics adoption decisions in FDD.

Resource slack

While the relationship between organizational slack and adoption is not clear-cut in general adoption literature (see Section 4.1.2.2), slack appears to have a positive impact on analytics adoption in the auditing domain (see Section 4.2.2). The same effect can be observed in the FDD field. The Big Four offer so-called analytics champion programs for technology-oriented consultants to participate in alongside their project work. These programs include trainings beyond the mandatory curriculum that empower the participants to not only apply the knowledge acquired to their project work, but also to promote acceptance by acting as contact persons, trainers, and ambassadors in their local offices *(SC2)*. In addition, the Big Four offer temporary assignments to their CoE teams *(M1, M2, SC5)*. These secondments should provide the consultants with the opportunity to gain a deeper understanding of the technical facets of analytics. After returning, the consultants can immediately apply the knowledge gained to FDD projects. They also serve as intermediaries between the transaction services teams and the CoE teams. This organizational leeway grants consultants the flexibility they need to build technical skills and promote adoption of analytics.[113]

Intra-organizational benefits through spillover effects

Finally, literature on analytics adoption in auditing suggests that adopting organizations may benefit from exchanging knowledge and sharing tools across the various service lines (see Section 4.2.2). Indeed, one expert refers to discussions with the firm's forensics team as the starting point to considering the use of analytics in M&A advisory *(P2)*. Aside from this example, however, no exchange of knowledge or tools takes place beyond the boundaries of M&A advisory *(M1)*. In particular, the interview partners emphasize the higher one-off use of analytics in the context of FDD than for other services[114] and the autonomous behavior of the Big Four's business

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[113] Note that analytics champion programs and secondments also constitute linkage structures that foster adoption (see the paragraph on "formal and informal linking structures" in this section).

[114] According to an interviewee, the purpose of the use of analytics solutions follows the DWH approach (~80%) rather than the data science approach (~20%) for most of the Big Four's projects across all their service offerings. In addition, the respondent explains that the large majority of analytics projects aims at repeated (~70%) rather than one-off use (~30%) *(D2)* (see Figure 5.4 in Section 5.2.1.4). According to this assessment, it appears logical that FDD hardly benefits from spillover effects across the various services offered by the Big Four firms.

units *(P2)*. This autonomy means that units act independently of one another and do not proactively share methods for analyzing data. Instead, the exchange of knowledge and tools primarily takes place between geographical territories and between the different services related to M&A transactions – especially for more decentrally organized companies *(M3, SC2, SC4)*.

5.3.2.3 Environmental context

In the original TOE framework, the environmental context consists of three factors: industry characteristics and market structure, technology support infrastructure, and government regulation. In prior literature on analytics adoption in auditing, it is suggested that client demand should also be examined, since audit firms operate as service providers. Moreover, as outlined in Section 4.2.2, FDD is less exposed to regulatory restrictions than auditing. Even so, the potential liability risks that may arise as a consequence of possibly increasing expectations towards the discovery of red flags must be tested for their validity in the due diligence context.

Industry characteristics and market structure

The investigation of industry characteristics and market structure focuses on the competitive situation. As indicated in Section 4.1.2.2, theory suggests that vigorous competition expedites technology adoption. This effect can be confirmed for analytics adoption among the Big Four as FDD service providers. An interview partner illustrates the significance of competition as a motivator for the adoption decision using the "better disrupt yourself than be disrupted by someone else" [translated from German] [35:15] *(P2)* mantra. In particular, there has been a fierce race among the largest four audit companies to be first mover and to reap the corresponding advantages *(P2, M1)*. These varying starting points for analytics efforts, coupled with different investment budgets, lead to slight differences among the four market leaders *(P1, D3, M3, SC3, SC4)*. Yet, the overall intense competition among these firms is a facilitating factor to increasing analytics adoption *(D4, M2, M3, SC5)*. Smaller auditing companies, in contrast, are lagging behind their larger competitors when it comes to introducing analytics. They are unlikely to catch up due to the compounding disadvantages in terms of size, human and financial resources, technical know-how, and back office infrastructure *(P1, P3, D3, D4)*. Instead, this could leave room for new players to enter the market of due diligence services. While one interviewee considers technology companies relevant *(M2)*, the vast majority of experts do not expect a market entry for two reasons. First, they consider the due diligence market or, more broadly, the M&A market too small to be of interest to technology companies when compared to other industries that these companies have tapped into in the past *(P1, D3, SC3)*. Second, they rate the market entry barriers as too high for companies that currently lack both functional and industry know-how *(D3, SC1, SC3)*.

Client demand

Client perception and demand of analytics-based due diligence services is largely nonexistent. The experts report that the corresponding service offerings are not well-known to the clients *(M2, M5, M6, SC3)*. That clients lack awareness traces back to the predicament that many changes brought about through analytics relate to data processing and not the output itself, which makes the changes less tangible to the client *(SC1)*. As a results, there is currently no significant market demand for more sophisticated analyses in FDD *(P1, P3, M1, M5, M6, SC1, SC2)*. Additionally, poorly or moderately data-driven target companies fear that greater disclosure, necessary for detailed analysis, could reveal previously unknown risks to the counterparty, as the targets may not have analyzed the data themselves *(M1, M2)*. There are also some concerns that additional, more value creation-oriented analyses will incur costs that – due to their hypothesis-driven nature – will not necessarily produce the desired result *(P1, D2)*. For these reasons, the scope of FDD is only slowly shifting towards the identification of value drivers and the determination of value creation potentials through stronger integration of operational and commercial topics, i.e., the prospective state as outlined in Section 5.2.11 *(P1, P2, D3)*.

Overall, a technology push into the market by the Big Four firms can be observed instead of a technology pull. The question arises why these firms pursue the increasing use of analytics in FDD. First, as outlined in Section 5.2.9, increasing data availability is pushing and sometimes even forcing them to use analytics tools instead of conventional spreadsheet-based software in order to deliver their analyses *(P2, M6)*. Second, they expect and anticipate a trend towards the use of analytics in FDD and want to create first mover advantages *(P2, M1)*. The companies realize positive benefits from applying analytics to previous projects and continue using analytics so as to also realize these benefits in other projects. Once analytics software has been applied in due diligence projects the clients also recognize their benefits. These perceptions are reported to be consistently positive, which, in turn, creates demand for using analytics in subsequent projects *(P2, P3, M2, M5, SC1, SC3, SC4)*. Thus, the service providers endeavor to lead the digitalization of this process and shepherd their clients through the transformation of the due diligence process *(P2, D1)*. They initially focus on private equity firms that are described to be most interested in post-deal value creation issues that are inherently linked to the use of analytics *(P2)*. An interview partner summarizes the relationship as follows:

> 'It is about reeducating the clients. However, this will not happen soon, as the clients still think in [functional] pots. […] They steer the [M&A] process through the various disciplines.' [translated from German] [49:53] *(P2)*

To conclude, client demand does not play a decisive role in the audit firms' decision to adopt analytics technology. Instead, these firms follow a technology trend that they anticipated ahead of their clients.

Technology support infrastructure

According to adoption theory, the availability of an infrastructure that supports technology usage is a facilitating factor (see Section 4.1.3.2). Accordingly, prior studies on the adoption of analytics in auditing place the availability of qualified personnel to the forefront (see Section 4.2.2). Analogously to auditing, this factor is essential to the decision to adopt analytics in FDD. As described in Section 5.2.10, both subject competence and technical skills are required. According to the interview partners, although their firms' employees did not initially possess the necessary skills to a sufficient extent, they were able to learn and improve their professional application within a short period of time through trainings and regular usage *(D4)*. The impact of individuals' technical skill levels on their adoption behavior is assessed in Sections 5.3.3.2 and 6.7.4.2, respectively.

Regulatory environment

Finally, while regulation can have both stimulating and detrimental effects on technology adoption (see Section 4.1.2.2), its impact in auditing is constrictive in nature. In auditing, regulation lags behind the technological opportunities, which creates ambiguities (see Section 4.2.2). By contrast, regulatory restrictions do not have a decisive impact on the use of analytics in FDD. Moreover, the increased possibility of identifying significant risks (deal issues) or even deal breakers does not lead to higher expectations concerning the detection of red flags that, if undetected, would increase litigation risk. This lies in contrast to the expectations in auditing. Instead, in FDD, the low number of litigation cases, paired with limitations of liability, confirms that this aspect has low decision-making relevance to the introduction of analytics *(M1)*.

5.3.3 Individual adoption factors

After deciding in favor of analytics software in FDD, an essential challenge the Big Four face in their plans to further enhance efficiency is how to increase adoption (see Section 5.2.10). Consequently, the following sections evaluate the core constructs of the UTAUT (performance expectancy, effort expectancy, social influence, facilitating conditions), the proxy of behavioral intention, and the moderating effects. The findings gained in the qualitative analysis, in combination with adoption theoretical considerations, are used to develop hypotheses, which are validated in the subsequent questionnaire.

5.3.3.1 Performance expectancy

As theory suggests, the expert interviews reveal that performance expectancy has a positive influence on adoption. Many experts agree that the majority of consultants recognize the benefits of using analytics software in FDD *(D1, M2, M3, M6, SC1, SC2, SC5)*. In particular, the companies' top management teams and partners frequently stress the need for and benefits of analytics to their co-workers *(D1, M1)*. They are also shifting towards using these aspects as selling points in client discussions *(D4, M2, M6)*.

However, the qualitative analysis reveals that the hierarchy level and experience with analytics could play moderating roles. In particular, it is reported that performance expectancy is lower for those senior managers and directors who have learned to perform FDD with a more traditional and less data-driven approach and have not yet applied analytics in practice *(P1, D1, M5)*. Those who have already tried analytics software may have had negative experiences in their first trials *(SC3)*. In addition, they do not yet have the necessary competences needed to verify the analyses performed by their co-workers. This is because those senior managers and directors are not used to working with a single version of the truth and trusting a black box logic that makes it difficult for them to follow individual calculation steps *(P1, M2, SC2)*. In addition to the cultural and experiential aspects, this group takes a more skeptical view of analytics as it has to bear the responsibility for many project-related factors. These factors affect the cost-benefit trade-off and determine whether the longer lead time of analytics will pay off (see Section 5.2.9) *(M6)*. Their lack of trust combined with the responsibility to meet client expectations (e.g., with regard to the discussion of interim results) is reflected in their project approach. For example, multiple project situations were described in which some consultants were instructed to use analytics software to take advantage of efficiency gains at a later stage and other consultants had to use traditional deal tools to generate intermediate results in parallel *(SC2)*. Another aspect that reduces staff performance expectancy is the lack of extrinsic motivation due to the absence of financial incentives for using analytics *(SC2)*. This applies in particular to senior managers and directors, whose variable components account for a larger share of remuneration than for lower ranking employees. The related factor of career incentives (e.g., faster promotions) is handled differently by the Big Four *(P2, D3, SC2, SC5)* and the qualitative analysis does not allow for any initial conclusions to be drawn.

In summary, the qualitative analysis shows that performance expectancy has a positive impact on adoption. Moreover, hierarchy appears to moderate this relationship. More senior employees (except for partners who are less involved in operational project work) have a higher skepticism towards analytics' performance expectancy than more junior colleagues. The hierarchy level is expected to positively correlate with age, which needs to be tested in the quantitative analysis of this thesis. The moderating effect of age would be in line with previous studies (Venkatesh et al., 2003). Finally, contrary to theoretical considerations that do not find experience to have a moderating role, more experience is expected to positively influence the impact of performance expectancy on the intention to adopt analytics technology. This leads to the following hypotheses:

> **H1:** The influence of *performance expectancy* on behavioral intention is positive.
>
> **H1a:** The influence of performance expectancy on behavioral intention is moderated by *hierarchy level*, such that the effect will be stronger for more junior employees (except partners).
>
> **H1b:** The influence of performance expectancy on behavioral intention is moderated by *age*, such that the effect will be stronger for younger employees.

H1c: The influence of performance expectancy on behavioral intention is moderated by *experience*, such that the effect will be stronger for employees with more analytics experience.

5.3.3.2 Effort expectancy

Underpinned by theoretical considerations and prior studies, the expert interviews reveal that effort expectancy positively affects adoption. Literature on analytics adoption in the auditing discipline highlights two factors that decisively impact the perceptions of effort: employees' skills and tool complexity (see Section 4.2.3). In contrast, only employees' skills, or lack thereof, play a crucial role in FDD *(P2, D2, M3, M6, SC1, SC2, SC5)*.

As in auditing, the skill set required of due diligence consultants has already changed considerably and will continue to change as adoption increases and technology evolves further *(SC3)*. In particular, there is an increasing need for technical skills in the areas of data management and visualization. Moreover, the required skills are likely to prospectively expand towards statistical knowledge and programming, i.e., capabilities that CoEs currently contribute. These skill requirements differ from the proficiencies that due diligence consultants obtain as part of their economics or business studies and thus a competence gap emerges *(D1, M5, SC3)*. The experts assume that consultants are in a position to acquire the new skills required through further training opportunities. According to expert estimates, the tipping point has not yet been reached for when it is no longer possible to train existing employees and employees with fundamentally different profiles are needed to conduct certain analyses of FDD (e.g., those that require programming) *(D1)*. Interview partners also observe that skill deficiencies are greater among higher-ranked *(M1, M2, M6)* and older employees *(P1, D3, M6)*. Thus, the interview findings point towards testing for hierarchy level and age as moderators in the survey portion of this thesis. Additionally, the skill requirements also change along the different hierarchy levels. While more junior employees need the aptitude to perform the actual analyses, more senior team members need review competences *(D1)* (see Section 5.3.3.1).

In order to close the competence gap described above, the Big Four rely on two central elements already highlighted in Section 4.2.3: (i) upskilling of current employees and (ii) adaptation of the recruitment policy.

The qualitative analysis shows that (i) trainings prepare the consultants well for the actual use of analytics. The interview partners underscore that there is a visible difference between those employees who only received standard trainings and those who participated in advanced trainings *(SM1, SC5)*. Overall, there exists a high willingness to enhance the skill set as well as high interest and curiosity concerning the work with analytics software *(D1, D4, M1, M2, M3)*. Even so, there are different levels of technical skills and IT affinity among the consultants *(SC3)*. This requires less skilled consultants to participate in more trainings alongside their regular project work *(SC2)*. Effort expectancy is therefore assumed to play a more vital role those team members with less analytics experience.

However, training results in a trade-off of different time horizons. Financial incentive structures result in a preference for projects that lead to short-term profits rather than for the long-term development of employees through trainings that would lead to the successful expansion of the business *(P3, SC5)*. The prioritization of current projects over training means that some employees are not sufficiently trained in the use of analytics software. As a result, analytics cannot yet be used in projects across the board and the practical application of content learned in trainings is made more difficult *(D2, SC1, SC5)*.

Besides upskilling existing employees, the Big Four (ii) have adapted their recruitment towards a greater emphasis on applicants' technical skills. Analogously to their auditing branches, the Big Four firms hire IT specialists (e.g., data scientists) for the CoEs, which are responsible for the selection and development of software solutions and, in some firms, for supporting consultants by performing complex analyses. While all Big Four firms are increasingly hiring specialists for the CoE teams, there is mixed evidence concerning changes in the recruitment of due diligence consultants. Two interview partners report a stronger emphasis on IT skills including programming *(M6, SC4)*, whereas another interviewee does not perceive changes in the recruitment process *(SC2)*.

To conclude, the qualitative analysis indicates that effort expectancy has a positive influence on adoption. Moreover, hierarchy level, age, and experience with analytics moderate this relationship. Older and more senior employees tend not to have the required IT knowledge and therefore tend to attach greater importance to the efforts they must make in order to be able to use the corresponding software. While the effect of hierarchy has not been tested in the original model, the moderating effect of age would be in line with previous studies (Venkatesh et al., 2003). Finally, in line with theoretical considerations, less experienced employees have wider competence gaps and consequently also put more emphasis on the efforts required to close these gaps. This leads to the following hypotheses:

> **H2:** The influence of *effort expectancy* on behavioral intention is positive.
>
> **H2a:** The influence of effort expectancy on behavioral intention is moderated by *hierarchy level*, such that the effect will be stronger for more senior employees.
>
> **H2b:** The influence of effort expectancy on behavioral intention is moderated by *age*, such that the effect will be stronger for older employees.
>
> **H2c:** The influence of effort expectancy on behavioral intention is moderated by *experience*, such that the effect will be stronger for employees with less analytics experience.

5.3.3.3 Social influence

The factor of social influence does not play a significant role in the adoption of analytics in the auditing context (see Section 4.2.3). In the FDD context, however, positive social influence appears to contribute to adoption *(D3, M1, M2, M3, M6, SC1)*. Concretely, as described in Section 5.3.2.2, the Big Four firms offer an analytics champion program for technology-oriented consultants to expand their technical skill set and act as points of contact, trainers, and ambassadors in their local offices. The experts highlight the positive perception and social recognition of such champions and analytics power users who are described as “avant-garde” *(SC1)*, “go-to people” *(D3, M3)*, or “role models” *(D3)*. In particular, their skills, helpful attitudes, and extracurricular engagement are appreciated by co-workers. This, in turn, leads to higher visibility to senior employees and ultimately to improved career prospects *(M1, M2, M3, SC1)*. However, the interviewees do not report a distinctive effect of social influence on moderating variables from the original UTAUT (gender, age, voluntariness, experience). This leads to the following hypothesis:

> **H3:** The influence of *social influence* on behavioral intention is positive.

5.3.3.4 Facilitating conditions

Adoption theory as well as previous literature from the auditing field suggest that facilitating conditions foster technology adoption (see Sections 4.1.3.2 and 4.2.3). Analogously, according to the interviewees, the (i) technical, (ii) personnel, and (iii) knowledge infrastructures support adoption in the FDD environment.

There is a positive perception of the (i) technical infrastructure *(M2)*. The availability of hardware *(M3)* and software is a given *(M1, M3, SC1, SC5)*. For example, the required licenses for Alteryx software are available for every consultant and licenses are selectively available for Tableau *(M3)*. Moreover, a repository of workflows and VBA-based macros exists *(M2)*. Existing legal prohibitions (e.g., concerning server locations for data security reasons) are well implemented without restricting the consultants' work *(M1, M2)*.

The availability of (ii) support staff is also a given *(D3, M1, M2, SC1, SC2, SC5)*. Analytics champions and the CoE team support the consultants in cases where complex analyses are required, while more routine tasks can be outsourced to SSCs.

Finally, the (iii) knowledge infrastructure is well-established in the Big Four firms, particularly in the form of knowledge repositories and available trainings *(SC1, SC2, SC5)*. The training courses are constantly being developed and some have been made compulsory in order to reach all employees *(P2, SC1, SC2)*.

The qualitative analysis shows that the positive perception of the support infrastructure fosters adoption. However, based on the interviews, no assertion can be made about the effects of potential moderator variables that are part of the original UTAUT (age, experience). This leads to the following hypothesis:

H4: The influence of *facilitating conditions* on actual usage is positive.

5.3.3.5 Behavioral intention

The role of intention as a predictor of usage behavior is well-established in technology adoption research (Venkatesh et al., 2003). Thus, the original UTAUT, which is designed for organizational contexts, focuses on intention. In contrast, the consumer-focused UTAUT2 incorporates the construct of habit, which is defined as "the extent to which people tend to perform behaviors (use IS) automatically because of learning" (Limayem, Hirt, and Cheung, 2007, p. 705).

Interestingly, some interviewees mention the term habit as a potential inhibitor for the adoption of analytics among the group of higher-ranked employees that are used to traditional approaches. However, the qualitative analysis shows that the effects of traditional behaviors are already reflected in the model as they ultimately contribute to the formation of the intention. This effect is described in more detail in the following paragraph. Overall, the habit factor cannot be considered independently.

As outlined in previous sections, senior managers and directors need review skills to ensure the quality of their teams' analyses (see Sections 5.3.3.1 and 5.3.3.2). To achieve this, a basic understanding of and experience with analytics software is required *(D3)*. However, the group of senior managers and directors is used to the traditional way of working in the context of FDD. This leads to a vicious circle: Due to the accustomed way of working, they lack analytics knowledge, which hampers the management of teams that use analytics, and thus, the conventional approaches are retained. This vicious circle can only be broken by acquiring analytics skills, which is hampered by a lack of openness to learning analytics skills – due to previous habits *(SC3, SC5)*. However, two experts emphasize that it is lower performance and effort expectancy (see Sections 5.3.3.1 and 5.3.3.2), paired with the absence of financial incentives and obligations to use analytics, rather than habit, that are key inhibitors in the decision not to use analytics and to stick with traditional approaches instead *(P2, D2)*. Therefore, habit is already included in the model. Concerning intention the following hypothesis is formulated:

> **H5:** The influence of *behavioral intention* on actual usage is positive.

5.3.3.6 Moderating variables

The roles of age and experience, as well as the newly introduced potential moderating effect of hierarchy level, have already been extensively discussed in the previous four sections. In contrast, the roles of gender and voluntariness are weakly addressed by the experts interviewed. Thus, their impact cannot be directly linked to the four core constructs of UTAUT based on the interviews conducted.

Analogously to Curtis and Payne's (2014) procedure for selected moderators, no prediction for the moderator gender is made. First, this variable is expected to be much more homogeneous than in typical adoption studies. For instance, Bierstaker et al. (2014) report that 71% of the auditors that participated in their study are male. Second, the expert interviews do not indicate a significant influence of gender.

Another moderating variable in the original UTAUT is the voluntariness of the use. The interviews show that over time there has been a shift from purely voluntary use to a stronger institutionalized push to use analytics. For instance, one Big Four firm plans to instruct their SSCs such that their output is directly provided in analytics software, which also forces consultants to use analytics *(P2)*. Some Big Four firms have introduced internal tracking to determine which projects need to use analytics *(P2)*. One national affiliate outside the German-speaking area has even implemented a mandatory revenue threshold that obliges the consultants to use analytics software for projects that pass this value *(D3, SC2, SC4)* (see Section 5.3.1). Even so, few interview partners emphasize the substantive role of voluntariness. In particular, in contrast to the original UTAUT, they do not link the voluntary nature to the core construct of social influence. Thus, no prediction for the moderator voluntariness is made.

5.3.4 Summary

Overall, analytics adoption on FDD commissions across the German-speaking area lies between 30% and 50% for the Big Four with an increasing trend. Besides project-individual factors (see Section 5.2.9), adoption differs by (i) initiator (buy-side vs. sell-side), (ii) deal size, (iii) country of the adopting organization, and (iv) sophistication of the tools used. According to the experts interviewed, analytics adoption is higher for (i) VDDs, (ii) large deals (with a more extensive FDD), (iii) the first-moving Anglo-American area, and (iv) data management and descriptive analytics solutions.

Subsequent to the investigation of the adoption level, its influencing factors are qualitatively examined. At the organizational level, a technology push into the market can be observed instead of a technology pull. Competitive pressure rather than client demand has triggered audit firms' decisions to adopt analytics in the context of FDD. Service providers are following the early recognized trend towards the use of analytics to create first mover advantages and thus competitive edges, a process that is propelled by increasing data availability. Among FDD service providers, size matters: The Big Four are leading the way. Although the widespread use of off-the-shelf software is largely associated moderate licensing costs, smaller audit firms lag behind their larger competitors due to disadvantages in terms of size, human and financial resources, technical know-how, and back office infrastructure. Among the leading four audit firms, those players with decentral organizational structures have created slight first mover advantages. However, the actual adoption across FDD projects is more difficult for decentrally steered firms as they lack alignment on a global scale.

The main findings for the technological context are summarized as follows:

- *Availability:* Compared to findings from the auditing literature (see Section 4.2.2), the reliance on standard tools is higher in FDD. Thus, the great availability, good compatibility with existing IT solutions, and moderate licensing costs of commoditized off-the-shelf tools facilitate adoption across all firm sizes.
- *Characteristics:* The usage of data analytics (an already existing technology) in FDD (a novel context) constitutes a synthetic type of innovation that moderately affects the existing FDD process. Despite their only marginal influence on firm-level adoption decisions, technology characteristics cause considerable processual changes. These changes put emphasis on audit firms' adaptability and their learning effects from first mover experiences with analytics during the implementation stage.
- *Cost-benefit ratio:* The effect of cost-benefit deliberations on firms' decisions to adopt analytics tools remains unclear, which is in line with mixed theoretical considerations of prior auditing-related studies. In a departure from prior literature, increased process efficiencies and speed are primarily used to conduct additional, detailed investigations and make it possible to offer a lower price in competitive situations without leading to revenue losses. Simultaneously, a new argument comes to the fore that is neglected in auditing literature: It remains unclear whether (or when) increased process efficiency (while maintaining a stable revenue base) will recoup the technical, organizational, and personnel investments associated with introducing analytics technology. Finally, opportunity costs, such as potentially losing such market share if an-

alytics services are not offered, are implicitly covered in the paragraph on “industry characteristics and market structure” related to the environmental context.

The following paragraphs resume the key results for the organizational context:

- *Formal and informal linking structures:* The interviewed FDD experts confirm evidence from prior adoption studies that decentralized organizational structures are better suited to the initial adoption decision, but demonstrate a weaker aptitude for the actual implementation. This finding is especially important because of the high variance in the degree of centralization across the Big Four firms’ transaction services advisory units and their respective national affiliates. The question becomes: How can decentrally steered firms increase the adoption across different parts of their organizations in order to keep their first mover advantages? One potential solution to create the necessary cross-organizational alignment is to foster linking structures. Especially those firms whose CoEs are mainly staffed with technical experts would benefit from (i) joint due diligence projects with CoE involvement, the (ii) expansion of analytics champion programs, and the (iii) expansion of CoE secondment opportunities.
- *Communications processes:* The top management and partnership promote the use of analytics across all Big Four players, especially if this behavior is encouraged by appropriate incentive structures. This, in turn, fosters adoption. In contrast, the experts describe a mixed attitude among senior managers and directors who bear the responsibility for deciding on analytics usage in individual due diligence projects. Hence, the perceptions of senior managers and directors are examined in detail when dealing with adoption at the individual level.
- *Firm size:* Despite the moderate licensing costs of widely used off-the-shelf analytics tools, non-Big Four audit firms lag behind their larger competitors in adoption. In particular, these firms do not have the personnel and financial resources to establish the back office teams (e.g., CoE, SSC) needed to offer technical trainings and to create and thenceforth roll-out process steps and workflows. These elements serve as the basis for standardization and automation of data preparation and analysis steps.
- *Resource slack:* In line with research from the auditing discipline but in contrast to general adoption literature, organizational slack has a positive impact

on analytics adoption in FDD. Sufficient organizational leeway serves as a precondition to granting consultants the opportunity to take part in adoption-enhancing technical trainings and institutionalized programs (analytics champions, job rotations).

- *Intra-organizational benefits through spillover effects:* Contrary to suggestions from prior studies in the auditing domain, potential spillover effects across various services offered by the Big Four influence neither adoption decision-making nor analytics implementation. The approach towards the usage of analytics (see Figure 5.4) differs too widely between FDD and other services. Instead, cross-organizational exchange is limited to an alignment across geographies and within the M&A advisory business.

Lastly, the key findings for the environmental context are summarized below:

- *Industry characteristics and market structure:* The competitive situation is fierce among the Big Four as FDD service providers. Consequently, competition expedites analytics adoption. However, the four industry leaders are well ahead of their smaller competitors and potential technology entrants. Smaller audit firms suffer from structural disadvantages in terms of size, human and financial resources, technical know-how, and back office infrastructure. Technology companies, such as BI providers, focus neither on niche markets such as due diligence nor, more generally, on the M&A market. Entry barriers in terms of know-how are also too high for technology companies.
- *Client demand:* Client demand is not a promotor of audit firms' decisions to adopt analytics technology. Clients lack awareness of the opportunities that analytics provides in the FDD process. This is because many processual changes are intangible as they relate to data processing and not to the output itself. Moreover, some target companies react with skepticism to requests to share larger amounts of data. However, once analytics tools are applied in due diligence projects, the clients recognize their benefits. As a result, audit firms strive to slowly introduce analytics-based due diligence services to their clients in order to create demand for their use in future projects.
- *Technology support structure:* The availability of qualified personnel is essential to audit firms' decisions to introduce data analytics technology. While before the adoption of analytics software in FDD there was a competence gap

for the necessary functional and technical skills to use analytics software, decision-makers expect that this gap could be closed through trainings and regular usage.

- *Regulatory environment:* Regulatory aspects and liability concerns do not play a significant role in adoption in the context of FDD. Regulation does not have the same constrictive influence on adoption that it has in auditing. In further difference from auditing, there is no detrimental impact of increasing expectations towards the enhanced possibilities of uncovering red flags. The litigation risk could be higher if these red flags are left uncovered.

The impact of the organizational adoptions factors is summarized in Table 5.5.

Table 5.5: Comparison of organizational adoption factors for analytics in audit firms

TOE core constructs	Adoption factors	Expected and observed relationship with adoption		
		TOE framework	Audit analytics literature	Interviews
Technology	Technology availability	+	+	+
	Technology characteristics	+/–[1]	not tested	none
	Cost-benefit ratio	not tested	+/–	+/–
Organization	Formal and informal linking structures	+/–[2]	not tested	+/–
	Communication processes (top management support)	+	not tested	+
	Firm size (incl. financial resources)	+	+	+
	Organizational slack	+/–[3]	+	+
	Intra-organizational benefits through spillover effects	not tested	+	none
External task environment	Industry characteristics and market structure (competitive situation)	+	+	+
	Client demand	not tested	+/–	none
	Technology support infrastructure	+	+	+
	Regulatory aspects (liability risks)	+/–	–	none

Notes:
1) Depending on the concrete distinction (e.g., creating incremental, synthetic, or discontinuous change), a technology's characteristics can either stimulate or inhibit adoption decisions.
2) While linking structures promote adoption decisions, organizational structure has a dual effect, i.e., decentralization foster adoption decisions, while centralization fosters subsequent implementation.
3) Slack has an inverted U-shaped relationship, i.e., a medium-level fosters adoption while low or high levels inhibit adoption.

Source: Own illustration

The qualitative analysis indicates that all four factors of the UTAUT promote adoption at the individual level. Performance expectancy is a decisive factor, especially for younger and more junior employees with higher levels of prior experience. The most critical determinant to increase the level of adoption, however, is effort expectancy. In particular, a competence gap is present for older and more senior employees who have little or no prior experience with analytics software. These co-workers accordingly attach high value to the effort expected to upskill. Social influence and facilitating conditions are also deemed to have a positive influence on adoption. Despite being decisive factors, these determinants are highlighted considerably less often by the experts in their interviews.

The key findings for each factor of the UTAUT are summarized below:

- *Performance expectancy:* The qualitative analysis indicates that performance expectancy positively affects the behavioral intention that leads to adoption. Moreover, it suggests that this relationship is moderated by (i) hierarchy level, (ii) age (due to its expected high correlation with hierarchy), and (iii) experience. The influence of performance expectancy on behavioral intention is expected to be stronger for lower ranked, younger, and more experienced consultants. The most crucial finding concerns the impact of hierarchy, a potential moderator variable that has neither been discussed nor tested in previous adoption studies. With the exception of partners who are less involved in the operational project business, employees at a more senior level are more skeptical about the use of analytics than staff at a more junior level. This is mainly due to a combination of insufficient experience, negative experiences, lack of skills, fear of not meeting client expectations, and lack of financial incentives. In contrast to theoretical considerations that do not regard experience as a significant moderator, more experience is expected to positively influence the impact of performance expectancy on the intention to use.
- *Effort expectancy:* In line with the theory-based expectations, the qualitative analysis indicates that effort expectancy has a positive influence on the behavioral intention to adopt. In contrast to the auditing discipline, however, only employees' skills (or lack thereof), but not the complexity of the tools, triggers the effort expectancy related to adequately working with analytics software. This above relationship is proposed to be moderated by (i) hierarchy level, (ii) age, and (iii) experience. It is expected that the influence of effort expectancy

on behavioral intention will be stronger for more senior, older, and less experienced consultants. These groups exhibit larger competence gaps and therefore assign more weight to the efforts needed to close these gaps.

- *Social influence:* In contrast to the auditing context, social influence seems to promote the behavioral intention to use analytics in FDD. Those consultants who use and promote analytics particularly strongly (e.g., analytics champions, power users) are perceived positively by their colleagues and superiors and experience social recognition. This leads to improved career prospects, which ultimately serve as a motivator for adoption by the consultants. In contrast to performance expectancy and effort expectancy, the interviewees do not comment on any moderating effects.
- *Facilitating conditions:* In line with adoption theory and previous auditing research, the qualitative analysis indicates a positive influence of facilitating conditions on analytics adoption in the FDD environment. The main drivers are (i) technical, (ii) personnel, and (iii) knowledge infrastructures. The interviews do not allow for the development of initial suggestions on moderating effects.

Besides the influence of the model factors as outlined above, the expected positive relationship between behavioral intention and actual usage must be considered. Finally, the original UTAUT and its expected relationships are slightly altered following the precedent set by Renaud and van Biljon (2008), who state that "UTAUT can be applied to any technology type but there is some value in speciali[z]ing the [model] for particular technologies" (p. 212). Although the majority of the hypotheses developed over the course of the qualitative analysis are line with theoretical considerations and results from prior studies, the following differences are included:

- The qualitative analysis points to expanding the UTAUT by *hierarchy level* as a moderator for performance expectancy and effort expectancy.
- The qualitative analysis reveals a positive influence of *experience*, which has been considered insignificant in the original UTAUT, as a moderator for performance expectancy.
- Unlike the original UTAUT, the qualitative analysis does not reveal a moderating effect of *age* and *experience* on social influence and facilitating conditions.

- Unlike the original UTAUT, the qualitative analysis does not reveal a moderating effect of *gender* on all four core constructs.
- Unlike the original UTAUT, the qualitative analysis does not reveal a moderating effect of *voluntariness* on social influence.

Based on the qualitative analysis, no hypotheses could be made about some theoretically established moderating relationships. Nonetheless, these relationships, which still appear plausible due to their theoretical foundation, are tested in the quantitative analysis in Section 6.7.4.2 in order to obtain a global picture of adoption.

Table 5.6 sums up the impact of the individual adoption factors.

Table 5.6: Comparison of individual adoption factors for analytics in audit firms (1/2)

UTAUT core constructs	Direct and moderating effects	Expected and observed relationship with adoption		
		UTAUT	Audit analytics literature	Interviews
Performance expectancy[1]	**Direct**	+	+	+
	Gender[3]	+		?[5]
	Age	–		–
	Experience	none		+
	Hierarchy level	not tested		–
Effort expectancy[1]	**Direct**	+	+	+
	Gender[3]	–		?[5]
	Age	+		+
	Experience	–	–	–
	Hierarchy level	not tested		+
Social influence[1]	**Direct**	+	none	+
	Gender[3]	–		?[5]
	Age	+		?[6]
	Voluntariness[4]	–		?[6]
	Experience	–		?[6]
Facilitating conditions[2]	**Direct**	+	+	+
	Age	+		?[7]
	Experience	+		?[7]
Behavioral intention[2]	**Direct**	+	+	+

Notes:
1) The effect of performance expectancy, effort expectancy, and social influence is measured on behavioral intention.
2) The effect of facilitating conditions and behavioral intention is measured in actual use behavior.
3) A "+" sign indicates that the effect is stronger for men; a "–" sign indicates that the effect is stronger for women.
4) A "+" sign indicates that the effect is stronger for voluntary settings; a "–" sign indicates that the effect is stronger for mandatory settings.
5) Based on the qualitative analysis, no prediction, if any, can be made about the effect of gender.
6) Based on the qualitative analysis, no prediction, if any, can be made about the effect of age, voluntariness, and experience in the context of social influence.
7) Based on the qualitative analysis, no prediction, if any, can be made about the effect of age and experience in the context of facilitating conditions.
Three-way interactions are not depicted in this table.

Source: Own illustration

6 Use and adoption of data analytics – A quantitative analysis

The sixth chapter contains the quantitative, questionnaire-based analysis of key aspects of the use and adoption of data analytics, which are selected from the preceding expert interviews based on their relevance. First, the basics of quantitative survey research are outlined (Section 6.1). Afterwards, the design and development of the questionnaire (Section 6.2) and the data collection process (Section 6.3) are described. In Section 6.4, data quality is evaluated and common biases are tested for. Next, the large, representative sample of 333 respondents (24.0% response rate) is presented (Section 6.5). Finally, Section 6.6 deals with the use of different data sources and analytics technology. In particular, the suitability of data analytics for FDD, trends in data availability and technology development, data and data analytics usage tendencies, and an outlook to the future provide a comprehensive and representative overview of applications of newly emerging technological opportunities. Moreover, this section highlights demographic and institutional differences. Finally, Section 6.7 concludes by addressing individual technology adoption with a covariance-based SEM of the UTAUT model, whose presumed interaction effects have been modified based on findings from the expert interviews. Sections 6.6 and 6.7 concerning the use and adoption, respectively, both conclude with a separate summary of the corresponding results.

6.1 Foundations of quantitative survey research

As a complement to the qualitative approach, this dissertation applies quantitative research, which has a deductive character (Goldenstein et al., 2018). The quantitative paradigm follows the goal of uncovering “structures through supraindividual contexts” [translated from German] (Raithel, 2008, p. 12).

The quantitative portion of this thesis aims to (i) measure and verify the phenomena identified in the expert interviews concerning the use of various data sources and data analytics technology in FDD and (ii) validate the hypotheses formulated in the previous chapter to extend the theoretical considerations to individual technology adoption in audit firms.

In the context of this thesis, a structured online questionnaire is applied to gain primary data. This large-scale survey instrument is an appropriate means for capturing generalizable results by collecting evidence from a representative sample (Black, 1999; Raithel, 2008; Remenyi, Williams, Money, and Swartz, 1998). This quantification allows for objective comparisons (e.g., between different subsamples) (Steiner and Benesch, 2018). Online questionnaires are a cost-efficient medium (Ilieva, Baron, and Healey, 2002; Raithel, 2008; Wagner-Schelewsky and Hering, 2019) that are more convenient for researchers and respondents. They also facilitate access to respondents and promise to achieve faster data collection and higher response rates than traditional, postal questionnaires (Ilieva et al., 2002). Respondents can take more time to answer questions or reconsider the responses they have given in the survey. As a result, they can reply more carefully than in an interview situation (Cooper and Schindler, 2013; Raithel, 2008).

6.2 Design and development of the questionnaire

The online questionnaire uses a cross-sectional design that is analogous to the design used in the expert interviews. This procedure is in line with the majority of prior research investigating adoption using UTAUT. In their review of UTAUT-related literature, Williams et al. (2015) show that 135 (78%) of the 174 papers examined use a cross-sectional approach.

The questionnaire is addressed to FDD consultants from large auditing companies in Germany, Switzerland, Austria, the Netherlands, and the U.S. The expert interviews identified national affiliates from the U.S. as technology pioneers. Responses from U.S.-based employees could therefore lead to valuable insights on cross-country differences. Unlike the expert interviews, the survey addresses the consultants from both the Big Four and Next Ten firms in order to investigate institutional differences. Addressees are identified by means of an extensive LinkedIn search based on their current employer, department, and territory.[115] The targeted sample should therefore be reflective of the population of FDD consultants working for large audit firms, the vast majority of whom are estimated to have LinkedIn profiles. The targeted sample thus be classified as a "list-based sample from [a] population with a high degree of coverage" [translated from German] (Wagner-Schelewsky and Hering, 2019, p. 792).

[115] LinkedIn, which is targeted at professionals, "tends to be used frequently by people in knowledge-intensive sectors such as […] consulting" (Blank and Lutz, 2017, p. 751). LinkedIn users do not significantly differ by gender and age and are more likely to have a higher income (Blank and Lutz, 2017). The platform is therefore likely to reflect the group of FDD consultants targeted in this study.

In order to reach a high (and representative) number of participants and to be able to query sensitive information, the anonymity of the respondents and confidentiality of their answers are emphasized in the introduction to the survey (Tyagi, 1989).

The questionnaire (see Figure A.17 in the appendix) is structured according to scientifically recognized standards (Porst, 2014). It begins with less critical questions, which are based on the participants' subjective assessments (icebreaker questions). The survey is then subdivided into four thematic groups (use of (big) data, use of data analytics tools, adoption/acceptance, implications and trends) to ensure the rigor of the response. In this part, the investigation of the first two research questions addressing the use of (big) data and data analytics is guided by the insights gained in the qualitative, explorative analysis. These insights were used to design the corresponding questionnaire sections specifically for this study. In contrast, the questionnaire section that deals with the latter two research questions related to technology adoption builds upon previous versions of the UTAUT model. It adapts established items for each construct to the specific context of this research. Demographic questions are asked at the end of the survey. Finally, a separate field is available for comments and criticism of the questionnaire.

The introduction and the four thematic sections contain 22 closed questions, followed by six demographic and one concluding question. Providing respondents with predefined possible answers makes them aware of aspects that they may consider important but may not be at the top of mind. It also reduces the time required for processing and minimizes the susceptibility to errors during data entry.

For most matrix questions that measure consent, 5-point Likert scales[116] are applied to facilitate faster decision-making and shorten the response time. This is essential to busy professionals of the targeted sample. Only the survey section dealing with adoption contains 7-point Likert scales in order to be consistent with prior studies. Using odd number of response options avoids forcing respondents in one direction, as is inevitable with scales that have an even number of scale points (Porst, 2014). Instead,

[116] The Likert scale is used to measure the personal attitude of survey participants. Through the symmetrical formulation of the answer options and the visualization along an equidistant scale, the results can be used as interval scaled within this thesis (Franzen, 2019; Häder, 2019; Schnell, Hill, and Esser, 2018).

the expert FDD advisors are trusted to give a free, conscious expression of their opinions. For rating scales that measure frequencies, impact, suitability, experience, or probabilities, proven pole formulations are applied (e.g., those recommended by Mummendey and Grau, 2014). In each case, only the poles are defined to facilitate intuitive responses along the scale (Hollenberg, 2016). Following the reading convention, the response's degree of intensity increases from left to right (Porst, 2014). Due to the use of established rating scales and the sufficient possibility for differentiation among five or seven response options, a metric scale level can be assumed for the measurement by fiat (Bortz and Döring, 2006).

For some questions, the scales are supplemented by a further answer option ("not applicable"), which could be ticked if the answer options offered were not relevant to the respondent or if the respondent did not wish to provide information. This element is intended to counteract any possible falsification of the results through item non-response (Porst, 2014).

Multiple half-open questions are also used to determine the meaning of individual facts by adding a residual category (e.g., "Others"), which opens a free text field. The use of this question type is particularly suitable when all possible answers to questions can be estimated, but cannot be conclusively defined (Züll and Menold, 2019).

The survey data concerning the use of data and analytics is examined with descriptive statistics and regression analysis. The data concerning adoption is analyzed using SEM, a common approach in empirical investigations dealing with UTAUT (45 applications (28%) in 174 studies examined) (Williams et al., 2015).

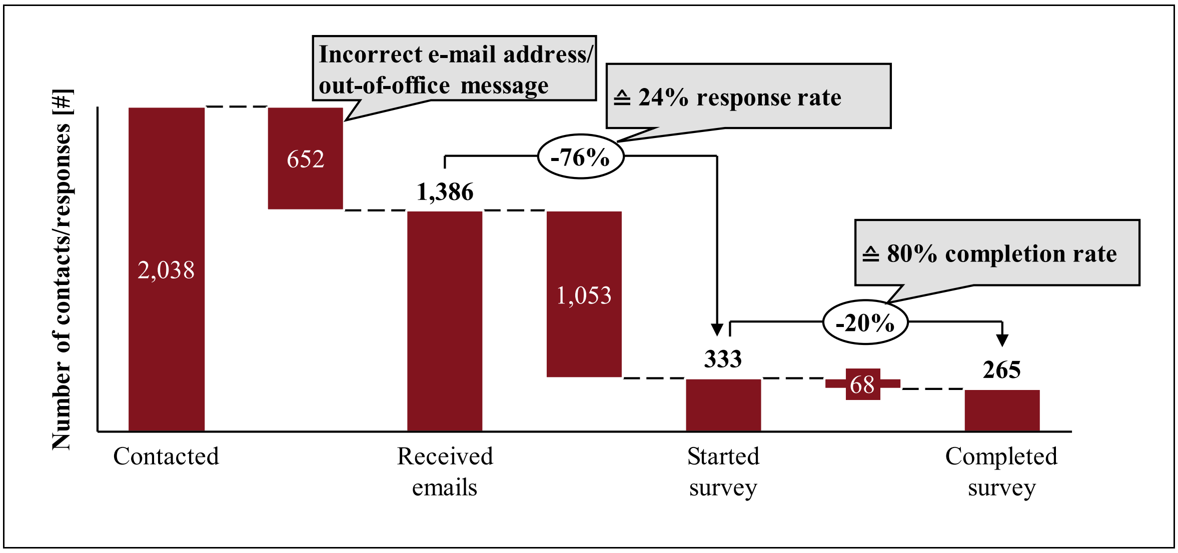
The survey instrument has been pre-tested with former interview partners as well as experienced survey researchers. These tests ensure comprehensibility, clarity, theoretical significance, feasibility under field conditions (including process of answer formation, interest, attention, duration), and the appropriate sequence of questions (Häder, 2019; Porst, 2014). Based on the feedback from the pre-tests, individual formulations were slightly modified and the adoption section was moved to the middle of the questionnaire. It contains several multi-item questions with a 7-point (instead of a 5-point) Likert scale, which were rated as less engaging by the people interviewed in the pre-test. Positioning this section centrally should keep the termination rate as low as possible.

6.3 Data collection

The survey was launched on October 4, 2019 and lasted three weeks until October 25, 2019. Both monetary and non-monetary incentives (exclusive access to survey results) were used to increase the response rate. Göritz (2006) finds in her meta-analysis that incentives in web studies motivate people to start the survey and that people are more likely to complete a survey they have accessed if incentives are offered. A reminder was sent two weeks after the survey was launched and also serves to achieve a high response rate (van Mol, 2017).

With a formal invitation letter (see Figure A.16 in the appendix), as well as a reminder letter two weeks after the launch, 2,038 people were invited to participate in the survey. 652 people could not be reached due to a lack of a valid e-mail address or an out-of-office message. Of the remaining 1,386 people, 333 took part in the survey, which corresponds to a response rate of 24.0% (see Figure 6.1). Compared to other technology-related studies among auditing professionals, this figure is very high and reflects the enormous interest in the subject matter.[117]

Figure 6.1: Sampling process

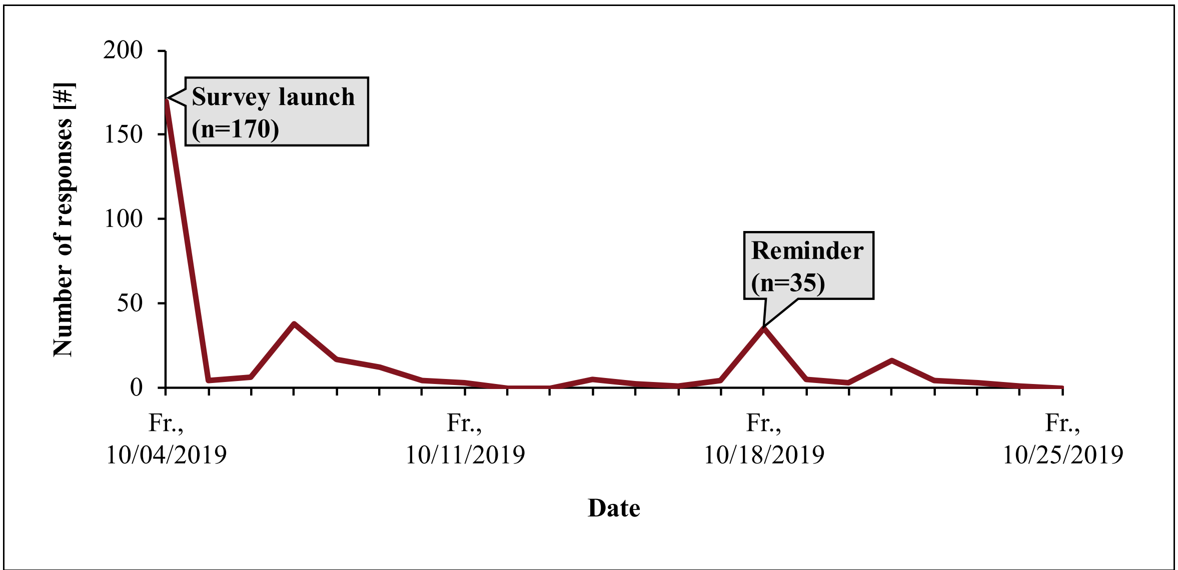


Source: Own illustration

[117] Recent studies among internal auditors received response rates of 2.3% (Gonzalez, Sharma, and Galletta, 2012), 9.1% (Li, Dai, Gershberg, and Vasarhelyi, 2018), and 11.6% (Kim et al., 2009), respectively. A survey among IT and financial audit practitioners obtained a response rate of 11.7% (Stoel, Havelka, and Merhout, 2012). A survey on technology adoption among external auditors led to a response rate of 13.1% (Rosli, Siew, and Yeow, 2016).

The majority of participants (170 or 51.1%, respectively) completed the survey on its launch date (see Figure 6.2). Three peaks in responses can be observed: one on the day the reminder e-mail was sent and two on the Mondays subsequent to the Fridays on which the invitation and reminder e-mails were sent.

Figure 6.2: Survey participation over time



Source: Own illustration

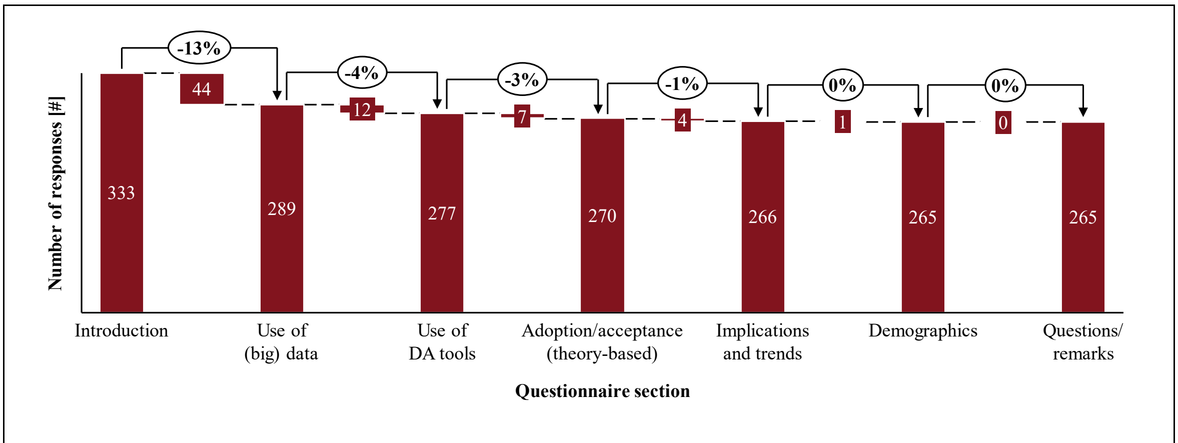
The survey was completed by 265 out of 333 participants who began the survey, which corresponds to a completion rate of 79.6% (see Figure 6.3). 44 out of 333 participants (13.2%) closed the questionnaire after completing the introductory section. The responses of the 44 dropouts to the first two questions posed in the introductory section did not differ significantly from the responses of all survey participants.[118] Few participants terminated the questionnaire prematurely in later sections of the survey.[119] It can therefore be inferred that the completion of the survey is not distorted by the respondents' personal attitudes to the importance of data analysis in FDD.

[118] The mean values for the first two questions are 4.43 and 4.05, respectively, for the drop-outs and 4.50 and 4.18, respectively, for the remaining participants. A two-sample t-test (two-tailed) reveals that there are no differences in the mean values of the two groups (p=0.4959 and p=0.3351, respectively).

[119] The different participation rates in the individual sections and the selection of the "not applicable" category (item non-response) lead to different sample sizes for the various items.

After initially screening the data with respect to patterns suggesting unreliable responses (e.g., very low response time, no variance because the same response category was selected for all items of a section), no cases had to be removed from the sample.

Figure 6.3: Response funnel



Source: Own illustration

6.4 Data quality

Before describing the data sample and analyzing the collected data, it is important to investigate possible systematic measurement errors. Therefore, common method variance (CMV) (Section 6.4.1), item non-response bias (Section 6.4.2), and non-representativeness (Section 6.4.3) are examined.

6.4.1 Common method variance

CMV describes the measurement error caused by the survey method (here: online survey) (Söhnchen, 2009). This systematic measurement error can lead to strong distortions in the relationships between independent and dependent variables. Söhnchen (2009) describes four different causes for CMV: (i) item characteristics, (ii) item context, (iii) survey context, and (iv) single source bias.

CMV in the (i) item characteristics and (ii) item context can already be taken into account through the formulations and positioning of the items chosen during questionnaire construction (see Section 6.2). The assurance of anonymity in the invitation e-mail and the cover letter of the questionnaire preemptively reduce a possible CMV that can be traced back to the (iii) survey context. This serves to strengthen the expression of subjective opinion by the respondents. A final possible cause for a CMV is the (iv) single source bias, i.e., the assessment of the independent and dependent variables by the same person. Due to individual views, social desirability, and the position in the company, distorted correlations may arise (Söhnchen, 2009).[120] Since an online self-report survey is the only data collection method used, Harman's one factor test is used as a diagnostic technique to check for a possible CMV (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003).[121] The test is based on the premise that CMV is present if only one factor is extracted in an explorative factor analysis or if a single factor explains a significant proportion of the covariance between the variables (Podsakoff et al., 2003; Söhnchen, 2009). In the exploratory factor analysis, the variables of the UTAUT model are taken into account. Further demographic information and nine variables that provide conclusions about the attitude towards analytics and its degree of utilization are also taken into account. The unrotated solution of the explorative factor analysis in the Harman's one factor test showed that six factors (eigenvalue > 1) could be extracted, with a single factor explaining no more than 43.8% of the total variance. Since neither a single factor emerges nor is the common threshold of 50% (Eichhorn, 2014) exceeded, it is concluded that CMV does not present a substantial concern.

6.4.2 Non-response bias

A unit non-response bias, i.e., that the respondents have fundamentally different characteristics than those not participating in the survey, would limit the general transferability of the results from the sample to the population as a whole (Armstrong and Overton, 1977).

One way of assessing the unit non-response bias is using a wave analysis to compare the response behavior of early and late respondents. This approach is based on the assumption that late respondents have a similar response behavior to non-responders. For verification purposes, the final data sample is divided into three equally large groups (Armstrong and Overton, 1977). A two-tailored t-test is used to compare the results of the first and last group. Of the 104 variables surveyed, only two indicators

[120] This problem can be avoided by measuring the answers from respondents to either only the dependent variables or only independent variables. However, this approach is also subject to significant limitations (Spector, 2006; Söhnchen, 2009).

[121] However, it should be noted that this diagnostic method is viewed critically by Podsakoff et al. (2003). Alternative, considerably more complex statistical methods for dealing with CMV are presented by Podsakoff et al. (2003) and Söhnchen (2009).

show differences in response behavior at a 5% significance level. It can thus be inferred that there is no substantial unit non-response bias in the sample.[122]

Furthermore, the presence of a self-selection bias is unlikely. The degree of experience and usage varies widely within the sample, implying that participation in the questionnaire was not limited to those interested and experienced in analytics or to analytics power users.

6.4.3 Non-representativeness

Finally, the completion sample (those that provided demographic information) is examined for representativeness. If the composition of the sample differs significantly from the population as a whole, potential bias may be present in the study results (Kaya and Himme, 2009).

The sample is examined on the basis of the three strata in order to determine whether certain groups are strongly overrepresented or underrepresented. These strata are: (i) type of organization, (ii) hierarchy level, and (iii) gender.[123] The Pearson's χ^2-test is employed to validate the goodness of fit and to identify potential differences between those people who received the invitation and reminder e-mails and the actual participants. Table 6.1 shows high similarities with regard to the type of organization (Big Four vs. Next Ten) and gender on a descriptive level, which the χ^2-test confirms is not significant on a 5%-level. However, Pearson's χ^2-test does reveal significant differences between the hierarchy levels (p=0.0000). In particular, the observed sample contains a lower proportion of partners and consultants and a correspondingly higher proportion of senior consultants and managers than expected. While the sample is representative in terms of organizational type and gender, generalizability across hierarchy levels may be limited. However, the need for a representative sample is not

[122] Because of the unequally distributed response times (see Figure 6.2), the sample was divided according to the time of response in an additional test. The first group includes those who responded within one week of sending the invitation e-mail (October 4-10, 2019), the second group includes those who responded in the following week (October 11-17, 2019), and the last group includes those who responded in the last week after the reminder e-mail (October 18-25, 2019). The two-tailored t-test that compares the results of the first and last group reveals that of the 104 variables surveyed, only seven indicators show differences in response behavior at a 5% significance level. Thus, the additional test confirms the absence of a substantial unit non-response bias.

[123] Note that the characteristics of age and service line could not be compared due to incomplete or missing information about those people who received the invitation and reminder e-mails. Moreover, the composition across the different service providers could not be compared since it was not requested during the questionnaire for anonymity reasons.

unanimously agreed upon in the literature as it competes with other sampling theories (Kaya and Himme, 2009). At least a slight deviation of the characteristics of the sample and the basic population is acceptable, as in the case with certain hierarchy layers in the present study (Diekmann, 2009; Laatz, 1993).

Table 6.1: Comparative validation of non-representativeness bias

Characteristic	E-mail recipients	Final sample
Type of organization		
Big Four	86.0%	90.2%
Next Ten	14.0%	9.8%
Hierarchy level/rank		
Partner	15.0%	6.4%
Director	9.2%	13.6%
Senior Manager	14.8%	13.2%
Manager	14.7%	23.0%
Senior Consultant	23.8%	31.7%
Consultant	21.9%	12.1%
Other	0.6%	0.0%
Gender		
Male	77.3%	76.7%
Female	22.7%	23.3%

Source: Own illustration

Overall, the data quality of the final sample can be considered good – with the necessary caveat regarding the distribution of hierarchy levels.

6.5 Data sample

This section briefly outlines the demographic characteristics of the final sample (see Table 6.2 and Table 6.3).

The proportion of participants working for the Big Four (90.2%) and the Next Ten (9.8%) approximately reflects the market shares for FDD services described in Section 2.2.3.4. The majority of participants work for the transaction services department that are primarily responsible for conducting FDD (86.8%). Approximately every tenth respondent stems from the deals analytics CoE teams (9.4%)[124] and the remainder work for other M&A-related teams (3.8%). The sample contains participants from all hierarchical levels from consultant to partner. The number of participants, which

[124] Note that only one of the 25 respondents who indicates affiliation with a deals analytics team is employed at a Next Ten audit firm. This can be seen as evidence of the minor role played by CoEs in non-Big Four firms.

tends to decline as the hierarchy level rises, is explained by the pyramidal personnel structure of the transaction service providers.

Study participants are located at all targeted countries outlined in Section 6.2. As can be expected based on the size of auditing organizations in Germany and the U.S., these two countries represent the largest groups with 141 and 60 participants, respectively. Although the corresponding national affiliates in Switzerland are significantly smaller, the participation of Swiss FDD consultants was surprisingly high (42 respondents). This can likely be traced back to the link between the study and the University of St. Gallen, a Swiss institution.

The average age is 32.3 years with a standard deviation of 7.3 years. The sample has a male share of 76.7% and a female share of 23.3%. This data appears to be representative when compared to samples from other studies. The average age among external auditors in the U.S. in surveys by Janvrin et al. (2008) and Bierstaker et al. (2014) is 36.5 years with a standard deviation of 10.0 years. The gender distribution in these surveys is also similar with 70.9% men and 29.1% women.

Table 6.2: Participant demographics – Categorical variables

Variable	Frequencies (absolute)	Frequencies (relative)
Type of organization		
Big Four	239	90.2%
Next Ten	26	9.8%
Service line		
Transaction services/due diligence	230	86.8%
Deals analytics/technology	25	9.4%
Other	10	3.8%
Hierarchy level/rank		
Partner	17	6.4%
Director	36	13.6%
Senior Manager	35	13.2%
Manager	61	23.0%
Senior Consultant	84	31.7%
Consultant	32	12.1%
Country[1]		
Germany	141	54.0%
Austria	12	4.6%
Switzerland	42	16.1%
The Netherlands	6	2.3%
United States of America	60	23.0%
Gender[1]		
Male	201	76.7%
Female	61	23.3%
Age[1]		
23-29	114	46.0%
30-66	134	54.0%

Notes:
Age was solicited as a continuous variable in the questionnaire. The above median split/dichotomization has been subsequently created to investigate interaction effects.
1) One or more participants did not answer the corresponding question.

Source: Own illustration

Table 6.3: Participant demographics – Continuous variables

Variable	n	Mean	Median	Std. deviation	Min.	Max.
Age	248	32.29	30	7.33	23	66

Source: Own illustration

6.6 Use of data analytics

This section deals with the survey questions, which address the use of different data sources and data analytics tools.[125] The observations made in the qualitative analysis can be tested on a large number of respondents that allows for drawing generalizable

[125] An overview of the summary statistics for both categorical and continuous variables is displayed in Table A.3 and Table A.4 in the appendix.

conclusions. The respondents' more granular demographic information also permits the study of institutional (type of organization, department, country) and personal (hierarchy level, age, gender) differences.[126]

The subsequent sections deal with the suitability of data analytics (Section 6.6.1), trends in data availability and technology development (Section 6.6.2), data and analytics usage tendencies (Sections 6.6.3 and 6.6.4), and potential analytics-induced changes in the future (Section 6.6.5). Finally, the key findings are summarized (Section 6.6.6).

6.6.1 Suitability of data analytics

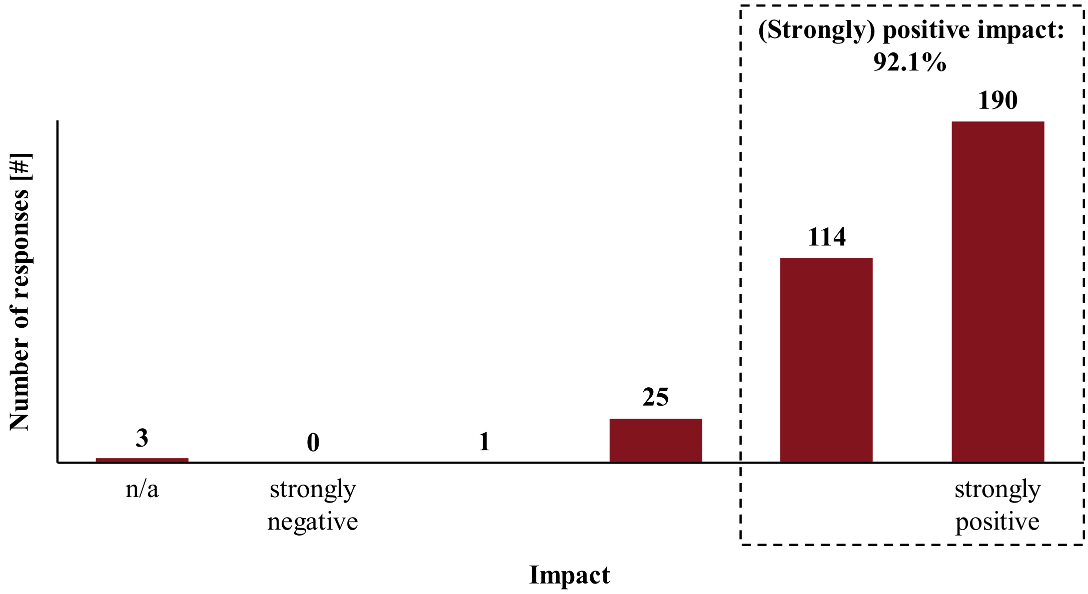
At the beginning of the questionnaire, 92.1% of the respondents indicate that data analytics software has a (strong) positive impact on the FDD process (mean: 4.49) (see Figure 6.4).[127] This unequivocal view underscores the relevance of the topic. Moreover, it can be observed that younger employees ($p=0.0215$), women ($p=0.0956$), and participants working in the U.S. ($p=0.0326$) evaluate the impact to be significantly higher.

[126] Such differences are tested using one-tailed t-tests of the following six demographic variables: type of organization (Big Four vs. Next Ten), department (transaction services/due diligence vs. deals analytics/technology), country (GSANL vs. U.S.), hierarchy level (consultant to manager vs. senior manager to partner), age (23-29 vs. 30-66), and gender. For the country, hierarchy level, and age variables, a binary variable has been created. The p-values indicated in the following sections refer to the one-tailed Student's t-test results.

[127] Here and in the following paragraphs, the terms strong and strongly, written in parentheses, denote that the percentage indicated refers to ratings of four and five.

Figure 6.4: Impact of data analytics on the FDD process

Question 1: How do you evaluate the impact of data analytics software on the FDD process? (n=333)

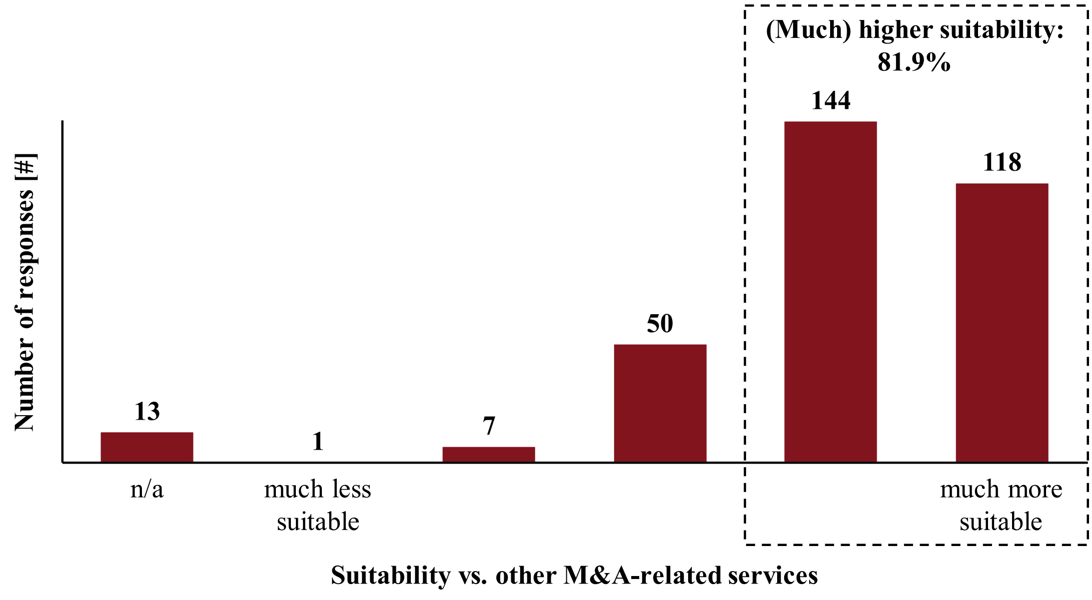


Source: Own illustration based on survey question 1

Participants also believe that the FDD process is well suited to the use of data analytics as compared to other M&A-related services. In concrete terms, 81.9% of respondents consider FDD to be (much) more suitable (mean: 4.16) (see Figure 6.5). Again, this clear view reinforces the relevance of the study at hand.

Figure 6.5: Suitability of data analytics for FDD

Question 2: In your opinion, how suitable is data analytics software for the FDD compared to other M&A-related services? (n=333)



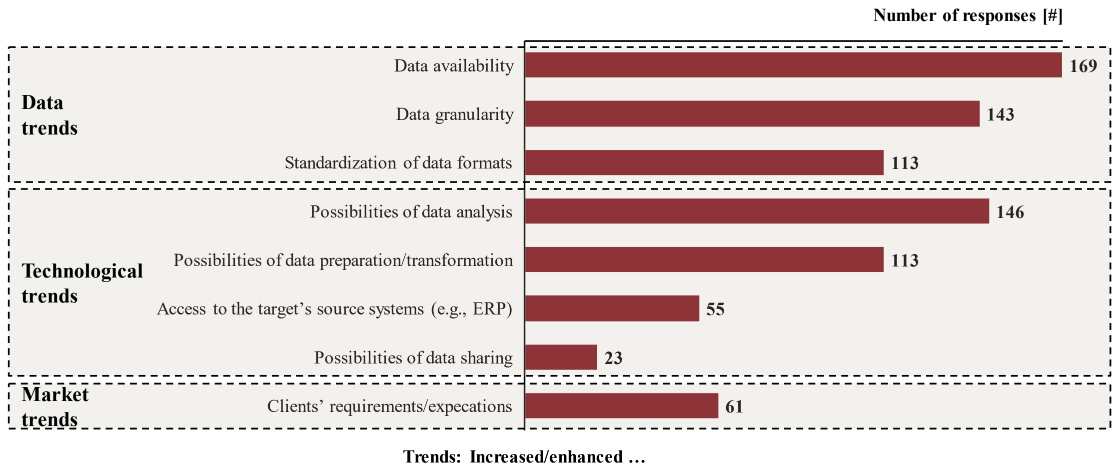
Source: Own illustration based on survey question 2

6.6.2 Trends in data availability and technology development

As illustrated in the qualitative analysis, trends in the data landscape, technological developments, and the market environment stimulate the use of data analytics. The results of the questionnaire make it possible to distinguish the strength of the various stimuli. They demonstrate that the primary drivers of data analytics are the rising availability of increasingly granular and standardized data and the enhanced data management and analysis possibilities (see Figure 6.6). One respondent emphasizes in the free text field that improving the user-friendliness of analytics tools (e.g., many operations no longer require programming skills) has contributed substantially to their use by FDD consultants. Enhanced data extraction through better access to the target's IT systems and facilitated data sharing, in contrast, only play a subordinate role. Moreover, as already stated in Section 5.3.2.3, client expectations are not an essential catalyst for the use of analytics tools. Interestingly, client demand plays a significantly greater role in the U.S. (p=0.0820), indicating that clients in Germany, Switzerland, Austria, and the Netherlands (GSANL) are less inclined to proactively request the use of analytics.

Figure 6.6: Stimulating trends for data analytics

Question 3: Which of the following trends most stimulate the use of data analytics in the FDD? *(Please choose up to three options.)* (n=289)



Source: Own illustration based on survey question 3

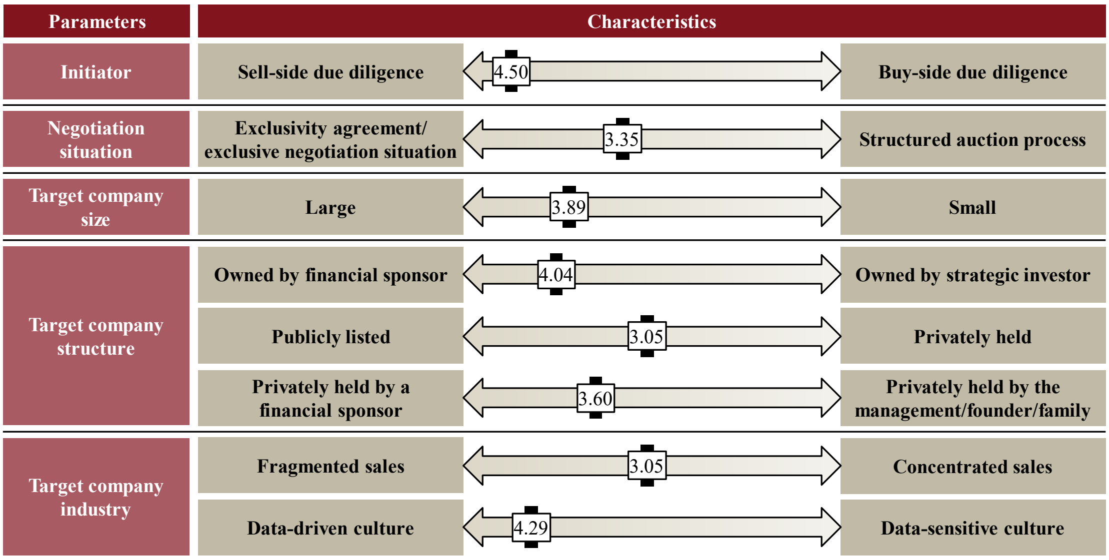
Since both the qualitative and the quantitative analysis underscore the crucial role of data availability, the question arises as to which determinants have the strongest influence on the data provided by the target company. Various factors are identified in Section 5.2.1.2 and their relative importance is measured in the large-scale survey (see Figure 6.7). The results reveal that the initiator (sell-side vs. buy-side) is by far the most important driver of data availability (mean: 4.50). Furthermore, data availability is mainly determined by the size of the target company (mean: 3.89), its owner (mean: 4.04), and its data culture (mean: 4.29). Data availability is expected to be particularly high in sell-side transactions with large, data-driven target companies held by financial sponsors. Overall, the different factors are weighted higher by FDD consultants from the U.S. (p=0.0230).[128] However, the judgement on better data availability in sell-side engagements is significantly higher in the GSANL region (p=0.0735). The disparity in data provision between sell-side and buy-side FDDs is stronger in the GSANL region and speaks in favor of more data-sensitive sellers in these countries. Finally, younger (p=0.0341) and more junior (p=0.0016) employees assign significantly higher values to the different drivers of data availability. This observation may be due to the fact that these groups tend to be more involved in data

[128] For one-tailed t-tests that comprise the mean of all items instead of the mean of single items, only complete responses, i.e., those without "n/a" answers for single items, are considered in order to ensure comparability.

preparation and analysis and therefore more aware of the different factors applicable to their daily work.

Figure 6.7: Determinants of data availability and granularity

Question 4: Do you agree with the following statements? Data availability and granularity are higher for … (n=289; mean values)



Source: Own illustration based on survey question 4

6.6.3 Data usage tendencies

After the previous consideration of the data availability, the usage tendencies of the target's financial and non-financial data, as well as data from external sources, are examined (see Figure 6.8). Financial data from the target company is used in virtually every FDD and form FDD's core (mean: 4.90). Internal non-financial data (mean: 3.94), financial data from external sources (mean: 3.05), and non-financial data from external sources (mean: 2.87) are used with decreasing frequency. The mean differences between each category are statistically significant (p=0.0000 for each comparison except for financial and non-financial data from external sources with p=0.0015). The observed ranking is consistent with the assessment derived from the interview data presented in Figure 5.2.

Although rated considerably lower, the inclusion of external information can be observed. In particular, external non-financial data, part of which falls under the definition of big data, is used with moderate frequency, underlining the practical relevance of research in this area. With respect to financial data from external sources, it can be determined that consultants working for Big Four firms use this data type significantly more often than those working for Next Ten firms (p=0.0867). Data usage of both financial and non-financial data from external sources is significantly higher in the U.S. (p=0.0632 and p=0.0607, respectively). The U.S.-based organizations, which are highlighted in the expert interviews as pioneers in the field of data analytics, are therefore fulfilling their role with regard to the inclusion of external data.

Figure 6.8: Overview of data usage in FDD

Question 5: How often is the following information used in the FDD? (n=289)

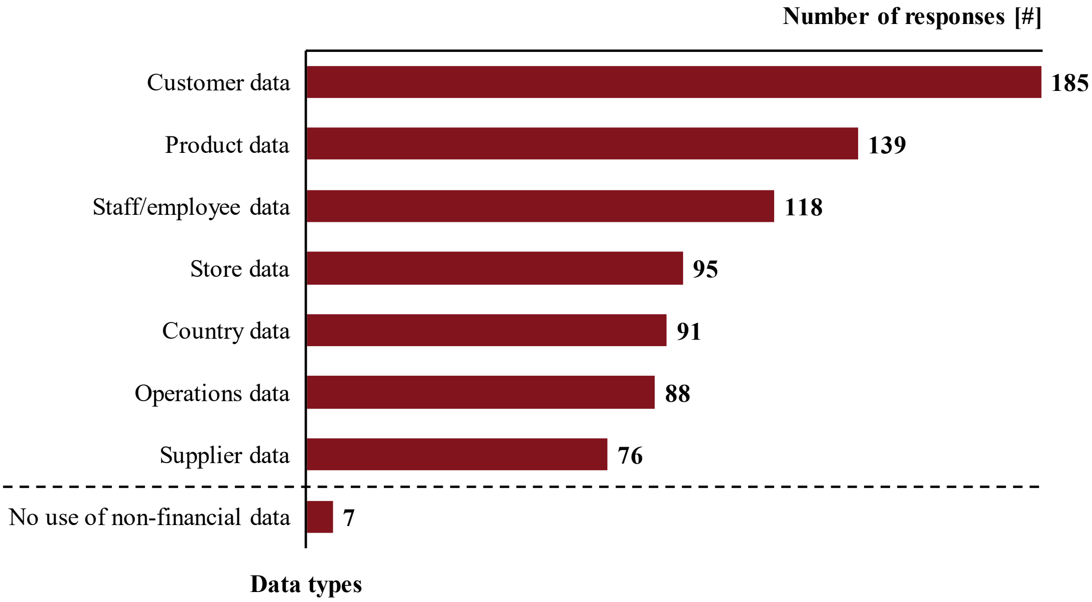
		Data sources	
		Target-internal sources	**Target-external sources**
Data focus	**Accounting/ financial data**	Average: 4.90 | Median: 5	Average: 3.05 | Median: 3
	Non-financial data	Average: 3.94 | Median: 4	Average: 2.87 | Median: 3

Source: Own illustration based on survey question 5

The contemporary importance of non-financial data is strengthened in the subsequent two examinations of the results. 282 out of 289 respondents (97.6%) report using non-financial data provided by the target company (see Figure 6.9). The most frequently used data types are customer data (185 mentions) and product data (139 mentions), which underscores FDD's evolving commercial focus. In contrast, production and supply chain-related information such as operations data (88 mentions) or supplier data (76 mentions) are used less often in FDD.

Figure 6.9: Usage of non-financial data from the target company

Question 6: Which of the following non-financial data of the target company do you most frequently incorporate into the FDD? *(Please choose up to three options.)* (n=289)

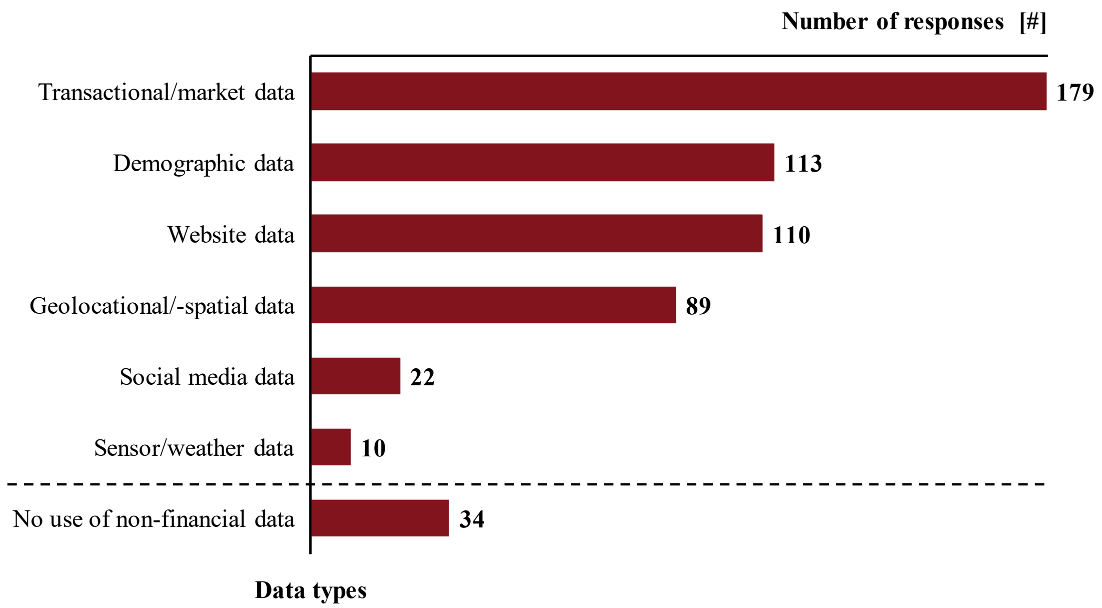


Source: Own illustration based on survey question 6

Consistent with the statements made concerning usage frequency in question 5 (see Figure 6.8), the usage of non-financial data from external sources is less prominent. Even so, 255 out of 289 survey participants (88.2%) report using such data (see Figure 6.10). Transactional and market data (179 mentions) are the most frequently used data types, which may be because they can be easily and logically linked to the financial and accounting data from the target company. Demographic data (113 mentions) and website data (110 mentions), which are mainly customer and product-oriented, are also popular. These observations again underscore FDD's shift towards the increasing integration of commercial aspects. Finally, social media data (22 mentions) is of minor importance, even though it is increasingly subject to accounting research.

Figure 6.10: Usage of non-financial data from external sources

Question 7: Which of the following non-financial data from external sources do you most frequently incorporate into the FDD? *(Please choose up to three options.)* (n=289)



Source: Own illustration based on survey question 7

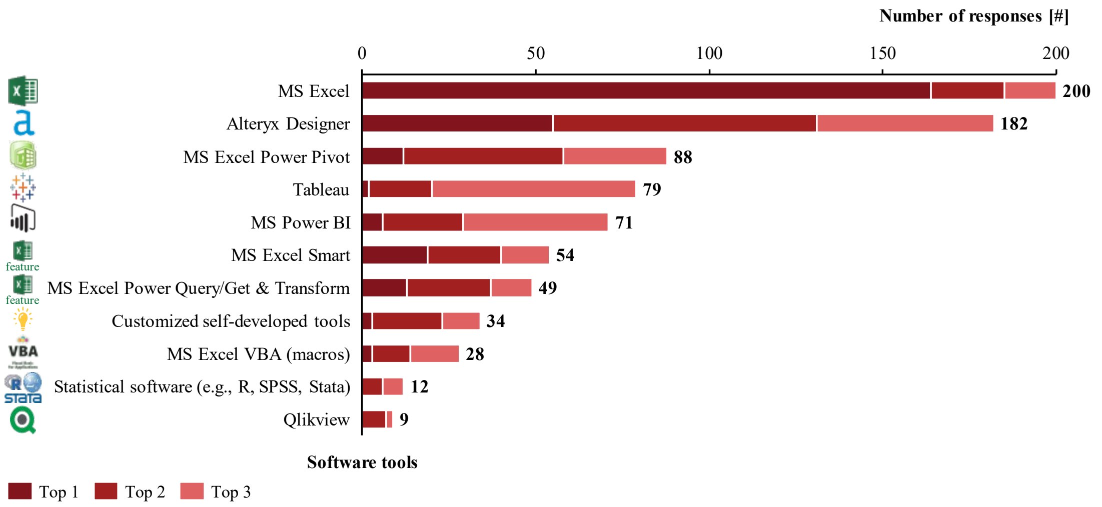
6.6.4 Data analytics usage tendencies

The shift towards a stronger inclusion of non-financial information and data from external sources observed in the expert interviews can be generalized on the basis of the survey results. Some of the data increasingly being used require the application of previously unexploited data analytics tools, while other data can still be analyzed easily using traditional software. For this reason, the tools currently employed in FDD are queried (see Figure 6.11). The results show that Microsoft Excel is (still) the predominantly used software tool to perform analyses in FDD. It has 200 mentions (164 thereof as top 1), which appears reasonable in light of the average usage rate of analytics software (49.9%, see Section 6.7.3.4). Alteryx Designer, which is primarily used for data preparation and transformation, occupies the second position (182 mentions) and is far ahead of Microsoft Power Pivot (88 mentions). These observations emphasize the current focus of analytics software use in FDD: data management. In contrast, tools that include visualization components such as Tableau (79 mentions; 59 thereof as top 3) and Microsoft Power BI (71 mentions; 42 thereof as top 3) are currently of lesser importance, supporting the conclusion drawn from the expert interviews. In-house-developed solutions (34 mentions) and statistical software (12 mentions) are of lesser importance at present.

Further analysis shows significant differences between the software solutions employed by the Big Four and Next Ten companies. Respondents from the Big Four firms list Alteryx Designer (p=0.0000) and the Microsoft Excel add-ins Smart (p=0.0043), Power Pivot (p=0.0327), and Power Query/Get & Transform (p=0.0737) among their three top-rated tools. In contrast, survey participants from the Next Ten companies rank Microsoft Excel (p=0.0014), statistical software (p=0.0001), and internally developed solutions (p=0.0000) among their three most frequently used tools. Thus, while the Big Four tend to use commercial software that facilitates the automation of analysis, the Next Ten use the traditional tool Microsoft Excel and employ software that requires a high degree of manual effort. In terms of visualization software, i.e., Microsoft Power BI, Qlikview, and Tableau, there are no significant differences between the two types of organization.

Figure 6.11: Preferred data analytics tools

Question 8: Which are the "top 3" most used software tools to prepare and conduct the analyses in an FDD? *(Please choose up to three options.)* (n=277)



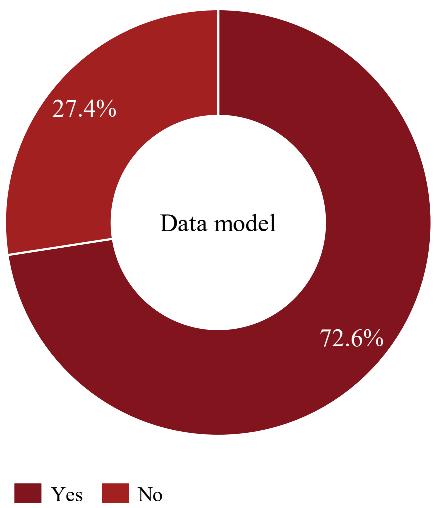
Source: Own illustration based on survey question 8

Building on the increasing use of data analytics tools, especially data management software, the following survey question explores the use of a data model as the single version of the truth. It reveals that approximately three-quarters (72.6%) make use of a data model approach (see Figure 6.12). In particular, the U.S.-based organizations make significantly more frequent use of data models than their counterparts based in the GSANL region (p=0.0156). Moreover, the deals analytics departments are significantly more likely to use data models than the transaction services departments (p=0.0768).

Interestingly, those who do not make use of data models (27.4%), find the impact of data analytics on FDD to be significantly lower (p=0.0000), assess FDD to be less suitable for applying analytics compared to other M&A-related services (p=0.0113), use data analytics software less often (p=0.0000), and are more likely to use MS Excel as their primary (i.e., top 1) software (69.7% vs. 55.2%). In summary, the more advanced employees and companies are in their analytics efforts, the more likely they are to use a data model approach.

Figure 6.12: Data model as single version of the truth

Question 9: Prior to the analysis with data analytics software, do you typically build a comprehensive data model ("single version of the truth")? (n=277)



Source: Own illustration based on survey question 9

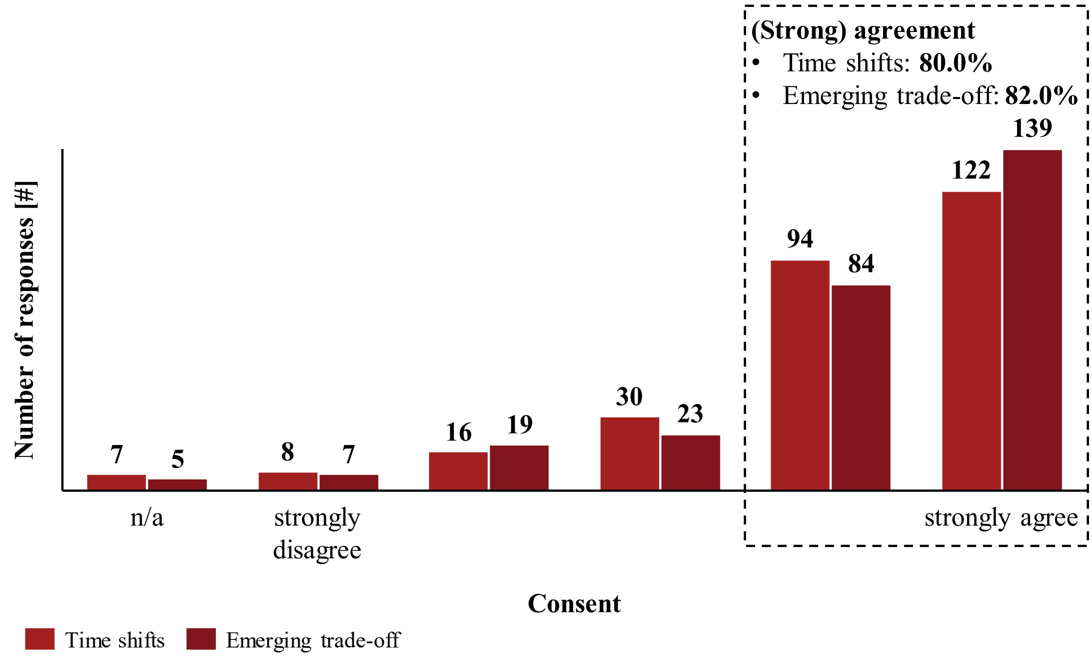
The qualitative analysis shows that the increasing efforts for data extraction, data cleansing, data transformation, and data mapping needed to build a comprehensive data model increase the lead time required prior to analyzing the data. On the other hand, the swift integration of updates, partially standardized and automated analyses, and the fast response to ad hoc requests lead to sizeable time savings during the analyses. These assessments are made by the interview partners and are shared by the majority of the survey participants. 80.0% of the respondents (strongly) agree that time shifts are caused by the use of data analytics approaches (see Figure 6.13). In particular, that time shifts are perceived significantly more strongly by respondents from organizations in the GSANL region (p=0.0004) and by respondents from Next Ten companies (p=0.0149). This can be seen as evidence that more technologically advanced employees (such as those based in the U.S. and from the Big Four firms) are already better able to cope with this change.

As explained in detail in Section 5.2.9, longer data preparation and shorter analysis lead to a trade-off; FDD consultants must consider whether the time savings realized in the analyses offset the longer lead time for data preparation. 82.0% of the respondents (strongly) agree with this view. The agreement is significantly stronger amongst the transaction services departments (p=0.0001). This is probably because the analytics specialists on CoE teams, who work with data analytics software by default, are less frequently confronted with this trade-off.

Figure 6.13: Time shifts in data preparation and analysis

Question 10: Do you agree with the following statement? The use of data analytics requires more time for data preparation (e.g., cleansing, transforming, mapping) and less time for data analysis (e.g., more standardization and automation, quick updates). (n=277)

Question 11: Do you agree with the following statement? Before using data analytics tools, FDD consultants must therefore consider whether the time savings in the analyses offset the longer lead time for data preparation. (n=277)

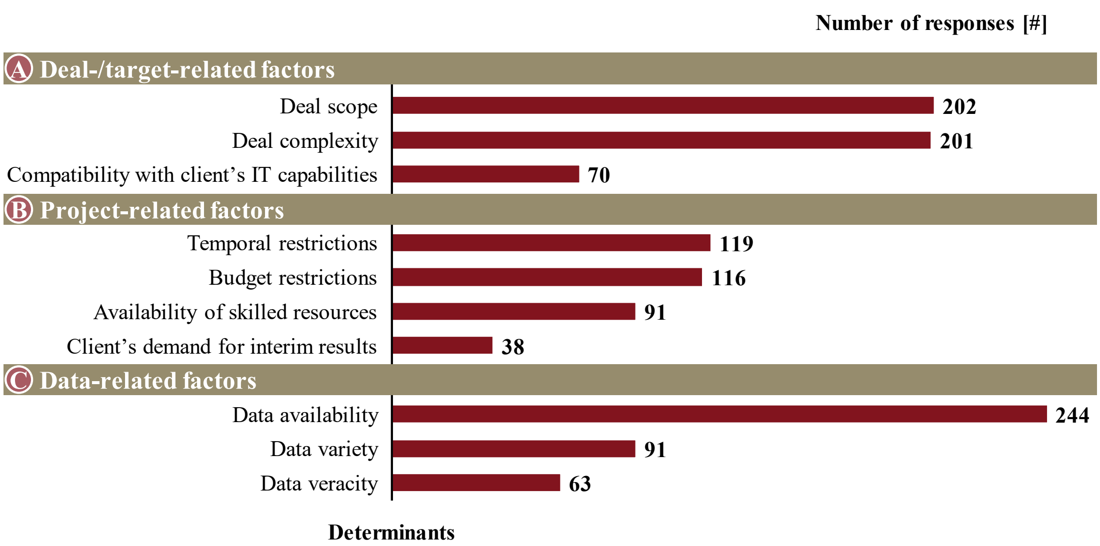


Source: Own illustration based on survey questions 10 and 11

The logical question arises as to which factors are used in the decision-making process to resolve this trade-off for individual projects. The various factors across three categories (deal-related and target-related factors, project-related factors, and data-related factors) that have been identified in the qualitative analysis (see Section 5.2.9) are tested. The questionnaire reveals that three factors have a major influence: data availability (244 mentions), deal scope (202 mentions), and deal complexity (201 mentions) (see Figure 6.14). For some of the decision-making criteria, institutional differences can be identified. For instance, time restrictions play a significantly greater role in the GSANL region (p=0.0000), indicating that the more technologically advanced U.S.-based organizations experience less difficulties meeting tight deadlines when using analytics tools. This observation is consistent with the finding presented in the previous paragraph, which demonstrates that the time shift is perceived much more strongly in the GSANL region. Moreover, Next Ten companies are more sensitive to budget restrictions (p=0.0323), which corresponds to the weaker financial position of smaller audit firms. Finally, data variety is a significantly more important decision criterion for the deals analytics departments (p=0.0075). This result appears logical, as analytics specialists tend to support regular FDD consultants by conducting complex analyses of semi-structured or unstructured data.

Figure 6.14: Determinants of the use of data analytics in project situations

Question 12: Which of the following factors do you take in account in the decision whether or not to use data analytics software? *(You can select any number of options.)* (n=277)



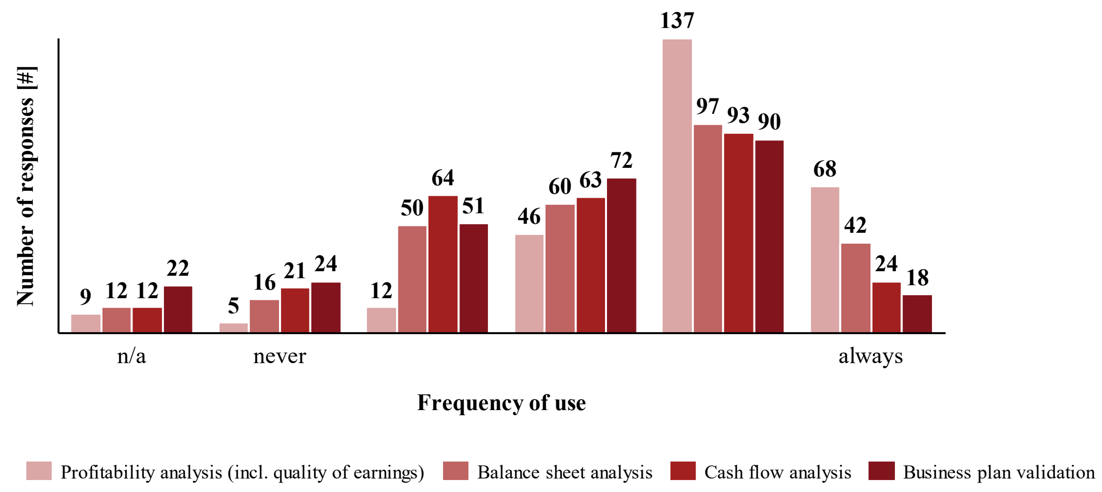
Source: Own illustration based on survey question 12

In those FDD projects in which the decision to use analytics is made, the profitability analysis (including the quality of earnings analysis) represents the main field of use (mean: 3.94) (see Figure 6.15). The balance sheet analysis represents the second most-used review area (mean: 3.37). Finally, the cash flow analysis (mean: 3.13) and business plan validation (mean: 3.11) exhibit the lowest application rate of data analytics tools.[129] This ranking confirms the descriptions from the expert interviews (see Section 5.2.3 et seqq.). These expert interviews also point to an increasing focus on value drivers and a linkage to commercial and operational issues in FDD. This focus is well-reflected in the current emphasis on using data analytics in the profitability analysis.

[129] Note that the mean differences between the different review areas are statistically significant for all comparisons (except between cash flow analysis and business plan validation).

Figure 6.15: Use of data analytics across review areas

Question 13: How often do you apply data analytics in the following review areas? (n=277)

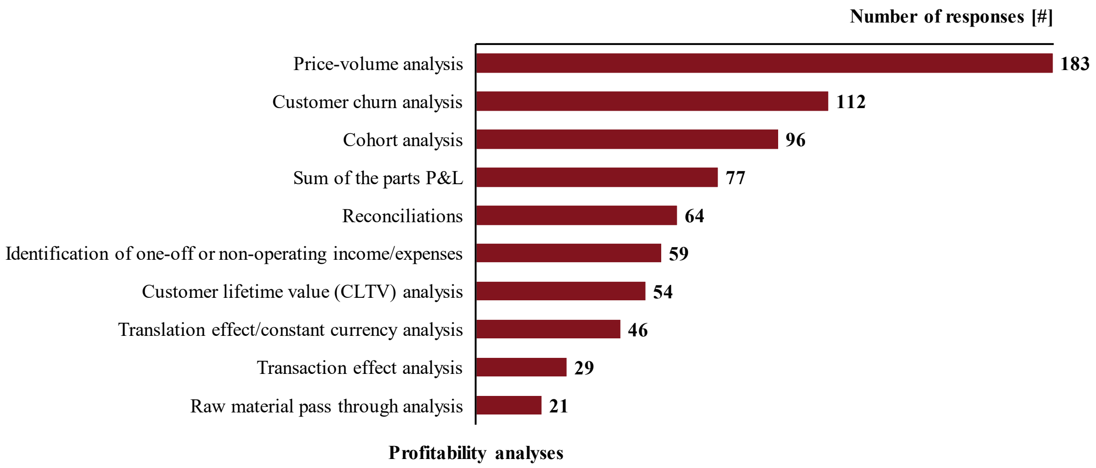


Source: Own illustration based on survey question 13

As outlined in Section 5.2.3, the profitability analysis is the key area for using data analytics in FDD. In particular, it benefits from both more granular data, especially from the target company, and analytics tools and techniques. Consistent with findings from the qualitative research, the price-volume analysis (183 mentions) benefits the most from these two components (see Figure 6.16). The customer churn analysis (112 mentions) and the cohort analysis (96 mentions) also benefit strongly. In summary, three commercially oriented analyses benefit most from using analytics in the setting of more detailed data, underscoring the growing linkage with CDD. By contrast, the operationally oriented raw material pass-through analysis, which was highlighted by four interview partners, plays only a subordinate role.

Figure 6.16: Profitability analyses benefitting from data analytics

Question 14: Which of the following profitability analyses will benefit the most from investigating more granular target data using data analytics tools? *(Please choose up to three options.)* (n=277)



Source: Own illustration based on survey question 14

6.6.5 Future outlook

After having examined the current state of data analytics applications, this section focuses on future perspectives. Trends regarding the use of analytics in FDD identified in the expert interviews and their implications for auditing firms and the FDD process are validated.

The agreement with the five predicted technological trends anticipated in the next five to ten years varies widely. Respondents had a (strong) agreement between 61.5% and 90.8% (see Figure 6.17).[130] The most likely development is the introduction of interactive dashboards as a supplement to the final FDD report (mean: 4.55), confirming statements by the experts interviewed that first dashboard solutions will be introduced as early as 2020. The future use of supplemental dashboards is much more likely for the Big Four (p=0.0144). Despite the difficulties described in Section 5.2.1.3, there is strong support for building out a global benchmarking database with data from previous assignments (mean: 3.89). The other three expected developments that receive less but still substantial, support are the use of predictive analytics to develop an alternative business plan (mean: 3.67), the full automation of key analyses

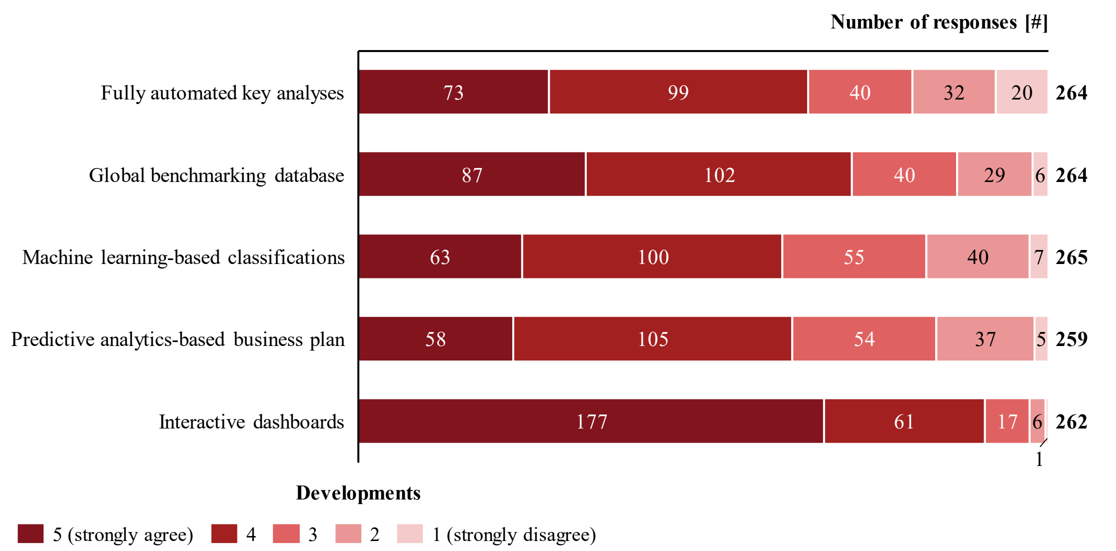
[130] The figures relate to the machine learning-based classification of items as normalizations or pro forma adjustments (61.5%) and the development of interactive dashboards as a supplement to the FDD final report (90.8%), respectively.

(mean: 3.66), and the use of machine learning-based classifications of items in the quality of earnings analysis (mean: 3.65). Of note, the full automation of key analyses is considered significantly more likely by lower-ranked employees (p=0.0452), i.e., those employees actually performing most of the analyses during an FDD project. Moreover, the development of business plans based on predictive analytics techniques by the audit firms themselves is rated as more likely by respondents from the Big Four (p=0.0596).

Overall, the agreement is significantly stronger for deals analytics departments (p=0.0068) and for U.S.-based organizations (p=0.0980). In particular, the deals analytics team members agree significantly more strongly with three trends: global benchmarking databases (p=0.0173), machine learning-based classifications (p=0.0004), and interactive dashboards (p=0.0697). The American employees show a significantly stronger agreement with two trends: global benchmarking databases (p=0.0458) and predictive analytics-based business plans (p=0.0289). These observations reveal that support for future technological developments depends on the employee's technology proficiency, which is higher among CoE experts and U.S.-based staff.

Figure 6.17: Future technological developments

Question 20: In your opinion, how likely will the following developments occur within the next five to ten years? (n=266)



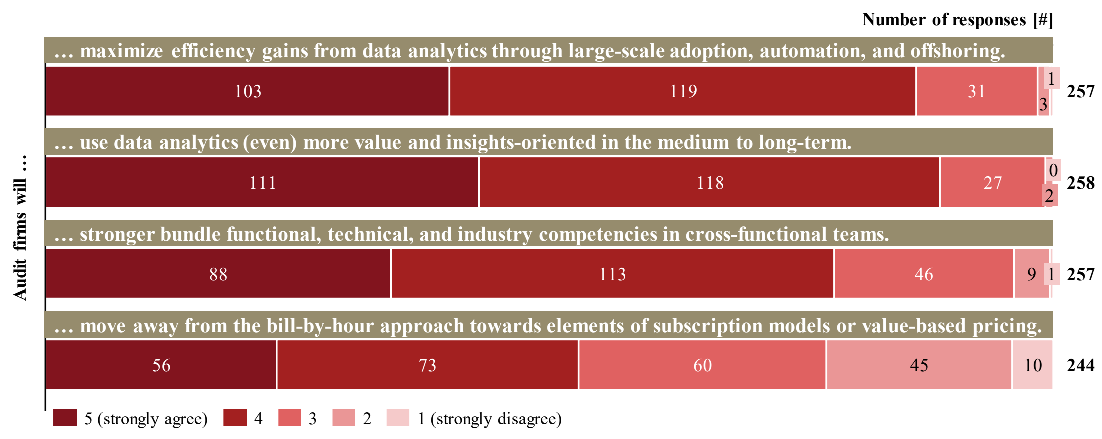
Source: Own illustration based on survey question 20

The next survey question deals with the implications of the increasing use of data analytics in FDD for audit firms. The first two statements receive the strongest support (see Figure 6.18). First, 86.4% of respondents (strongly) agree that audit firms will maximize efficiency gains through fostering adoption, raising the degree of automation, and increasingly using of offshore service centers (mean: 4.25). Second, 88.8% of participants (strongly) agree that audit firms will change their view in the medium-to-long-term: Firms will shift from an efficiency-oriented towards a more value and insight-oriented use of analytics in FDD (mean: 4.31). The predicted increase in the use of analytics tools and a more value-based perspective should stimulate demand for greater technical and industry expertise. Concurrently, 78.2% of respondents (strongly) agree that the stronger bundling of competencies in cross-functional teams will occur (mean: 4.08). The fourth statement on the impact of using analytics is regarded as more controversial by the respondents. Only 52.9% of survey participants (strongly) agree that traditional time and materials pricing will be replaced by new approaches (e.g., subscription-based or value-based pricing) (mean: 3.49). The comparatively lower support for this possible change is in line with expectations set by the expert interviews. In the interviews, for example, only a few experts take up this topic and they consider new pricing models to be in the nascent stage of development. However, it can be observed that higher-ranked employees significantly more strongly agree with the statement that the billing model will change ($p=0.0324$). This insight carries more weight as these higher-ranked employees are more likely have greater insight into strategic topics. Moreover, this statement receives significantly greater support from members of the deals analytics teams ($p=0.0049$) and from U.S.-based staff ($p=0.0018$).[131]

[131] Note that across all (equally weighted) potential developments, the deals analytics departments and U.S.-based organizations show a significantly stronger agreement ($p=0.0441$ and $p=0.0174$, respectively).

Figure 6.18: Impact of the use of data analytics on audit firms

Question 21: Do you agree with the following statements? Audit firms will … (n=266)

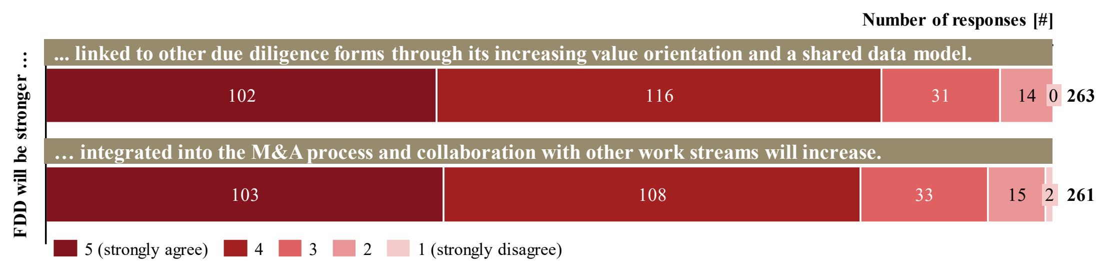


Source: Own illustration based on survey question 21

In the expert interviews, increasing linkages of FDD to other due diligence forms, especially commercial and operational due diligence as well as a stronger integration into the M&A process could be observed. Both future developments are largely supported by the questionnaire participants. While 82.9% of respondents (strongly) agree with tighter links between the different DD forms (mean: 4.16), 80.8% (strongly) agree with a closer collaboration with other work streams in the M&A process (mean: 4.13) (see Figure 6.19). Overall, these trends are more strongly supported by employees based in the U.S. (p=0.0023) and the deals analytics departments (p=0.0952).

Figure 6.19: Impact of the use of data analytics on FDD and M&A process

Question 22: Do you agree with the following statements? FDD will be stronger …



Source: Own illustration based on survey question 22

6.6.6 Summary

The findings of the questionnaire sections, which address the use of different data sources and data analytics tools, underline the relevance of the topic at hand. Overall, the survey results corroborate the findings from the expert interviews. They also allow for drawing statistically inferred conclusions about institutional and personal differences.

The impact of data analytics on the FDD process (92.1% (strong) agreement) and its suitability for FDD (81.9% (strong) agreement) are undisputed among respondents. In particular, changes in the data landscape (data availability, granularity, and standardization of formats) and technological developments in the functionality and ergonomics of data management and analysis software are driving the rise of data analytics. In contrast, client demand does not considerably stimulate the use of the corresponding tools and techniques, especially in the GSANL region, suggesting a supply-driven technology push into the market.

Data availability, the most important enabler of analytics, is primarily determined by the initiator of FDD projects. Sell-side due diligence engagements allow for substantially better data access than buy-side projects. The gap between these two forms is significantly wider in the GSANL region, suggesting that sellers in this region are more restrictive about granting access to data. Other key determinants of data availability include the size of the target company, its owner, and the data culture.

As expected, data from the target company are more frequently used than data from external sources and financial data is used more frequently than non-financial data. The survey results also reveal that external sources are included much more frequently by the U.S.-based employees. These analytics pioneers point the way to a possible similar development in the (currently laggard) GSANL region in the future. Although the use of non-financial information in FDD logically falls short of the use of financial data, the usage figures are remarkable and surpass the expectations generated in the expert interviews: 97.6% of respondents have already used internal non-financial data and 88.2% have already used external non-financial data in FDD. The most frequently used data is customer and product data (target-internal) as well as transactional/market data, demographic data, and website data (target-external). The frequent use of these customer and product-focused data types underscores the increased commercial focus of FDD analyses. As a result, the profitability analysis, especially price-volume, customer churn, and cohort analyses, primarily benefits from the application of data analytics.

The analysis of larger amounts of less structured data requires novel software solutions. Microsoft Excel, which is still the predominantly used software tool, especially for Next Ten firms, is often supplemented by add-ins for extended data modeling, especially Microsoft Power Pivot. Alteryx Designer is now established as the data preparation and transformation tool of choice. This result underscores the contemporary focus of analytics software use in FDD: data management. Data visualization tools, in contrast, are still less popular. Rarely used at present, the statistical software and self-developed solutions are, however, in greater use by Next Ten firms. With the increased focus on data management, data models are becoming part of FDD and are used by about three-quarters of the respondents. Those who do not follow the data model approach show a less positive attitude towards data analytics, use it less, and rely more on the traditional software solution Microsoft Excel.

The increased use of data analytics and the often accompanying development of a comprehensive data model lead to time shifts within the FDD process (longer lead times for data preparation, faster data updates and analyses). Employees in the GSANL region and employees of Next Ten companies, respectively, evaluate these time shifts significantly stronger. This indicates that they are less well prepared to cope with the changes to the FDD process. The time shifts result in a trade-off between the time-related advantages and disadvantages of using data analytics. Three of the factors identified in the expert interviews contribute significantly to resolving this trade-off: data availability, deal scope, and deal complexity. The assessment of other factors reveals strong institutional differences: Time constraints are significantly more important in the less technologically advanced GSANL region, budget restraints play a greater role for the less financially well-equipped Next Ten companies, and data variety is of higher importance for the data analytics departments dealing with more complex data sets.

The overwhelming majority of respondents (86.4%) (strongly) agree that audit firms will maximize efficiency gains in the short term. This focus helps audit firms to decide more often in favor of using analytics based on the trade-off outlined in the previous paragraph, thereby increasing adoption. In addition, audit firms strive to facilitate data management activities by increasing the level of automation and by leveraging offshore resources in SSCs. In the medium-to-long-term, 88.8% of survey participants (strongly) expect the use of analytics in FDD to become more value and insight-oriented. Five technological trends, especially interactive dashboard solutions as a supplement to the final FDD report, are widely supported by the survey. The level of support is significantly higher for U.S.-based staff, data analytics teams, and the Big Four. This indicates that organizations with a higher level of analytics use are already more convinced that additional technological innovations will be developed in the future. While the growing sophistication of analytics solutions increasingly requires technical expertise, the emphasis on value creation creates a call for greater industry expertise. Consequently, there is strong support among FDD consultants for the increased bundling of competencies in cross-functional teams in the future. The survey also confirms the trend towards a stronger link between FDD and other activities in the M&A process in general, and different forms of due diligence in particular. The technological, process-related, and organizational changes described in this chapter and previous chapters could lead to a shift in the business model of FDD service providers. However, possible adaptions to traditional time and materials pricing is the least supported trend, a result in line with findings from the expert interviews. Yet, support does exist for pricing modifications, at least among the technologically more advanced U.S.-based organizations, deals analytics departments, and more senior executives with greater insight into strategic matters.

The possible future developments described depend on the large-scale adoption of analytics, which is analyzed in the following section.

6.7 Adoption of data analytics

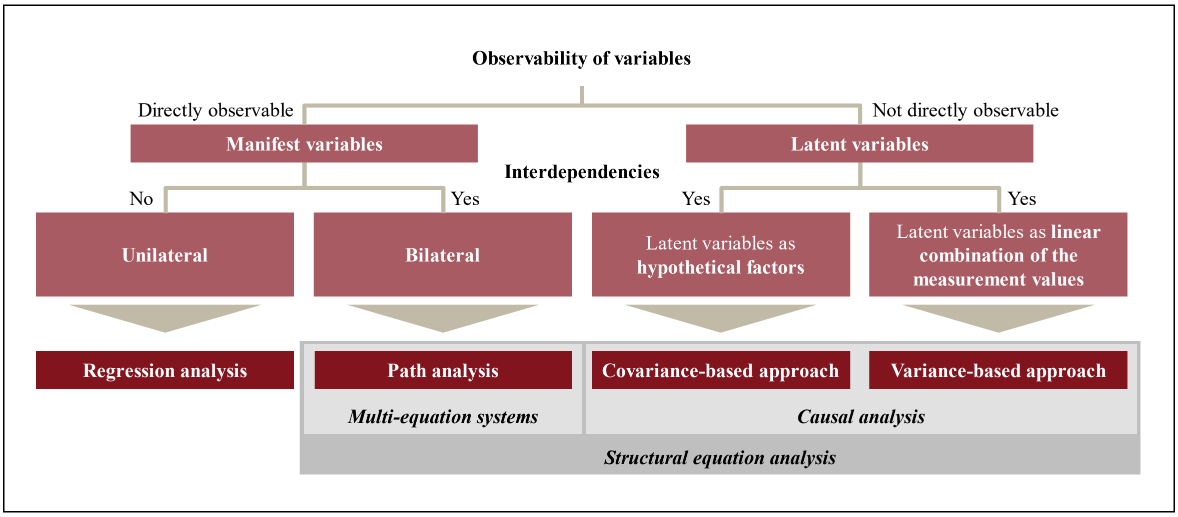
Building on the investigations of the qualitative analysis (see Section 5.3), the individual adoption of data analytics in FDD is also examined using quantitative methods. The hypotheses arising from the UTAUT model and developed on the basis of expert interviews are tested. However, the constructs of the UTAUT model, such as the behavioral intention to use analytics tools, are not directly observable. Therefore, the relationships between these unobservable constructs (i.e., latent variables) are analyzed using a SEM. Due to its theoretical foundation and the a priori refinements resulting from the expert interviews, the SEM analysis has a confirmatory (as opposed to an explorative) character (Backhaus, Erichson, and Weiber, 2015; Weiber and Mühlhaus, 2014).

The following sections provide an introduction to the fundamentals of SEM (Section 6.7.1), reiterate the adapted UTAUT model and the hypotheses developed (6.7.2), validate the measurement model (Section 6.7.3), and finally, evaluate the results of the structural model (Section 6.7.4) and a robustness test (Section 6.7.5). The main findings are subsequently summarized (Section 6.7.6).

6.7.1 Foundations of structural equations modeling

As referenced in the introduction, the analysis of individual adoption is based on constructs that are not directly observable. For the analysis of these latent variables, an SEM in the form of a causal analysis is recommended (see Figure 6.20).[132] In addition to the examination of latent instead of manifest variables, causal analysis distinguishes itself from classical regression analysis primarily through the successive or simultaneous investigation of multiple causal hypotheses (multi-equation model) (Backhaus, Erichson, Plinke, and Weiber, 2018; Backhaus et al., 2015; Weiber and Mühlhaus, 2014). Thus, SEM belongs to the "complex methods of multivariate analysis" [translated from German] (Backhaus et al., 2018, p. XII).

Figure 6.20: Methods of SEM



Source: Own illustration based on Weiber and Mühlhaus (2014)

As illustrated in the path diagram in Figure 6.21, two models, a structural model and a measurement model, are necessary to analyze the latent variables and the causal relationships between these variables:

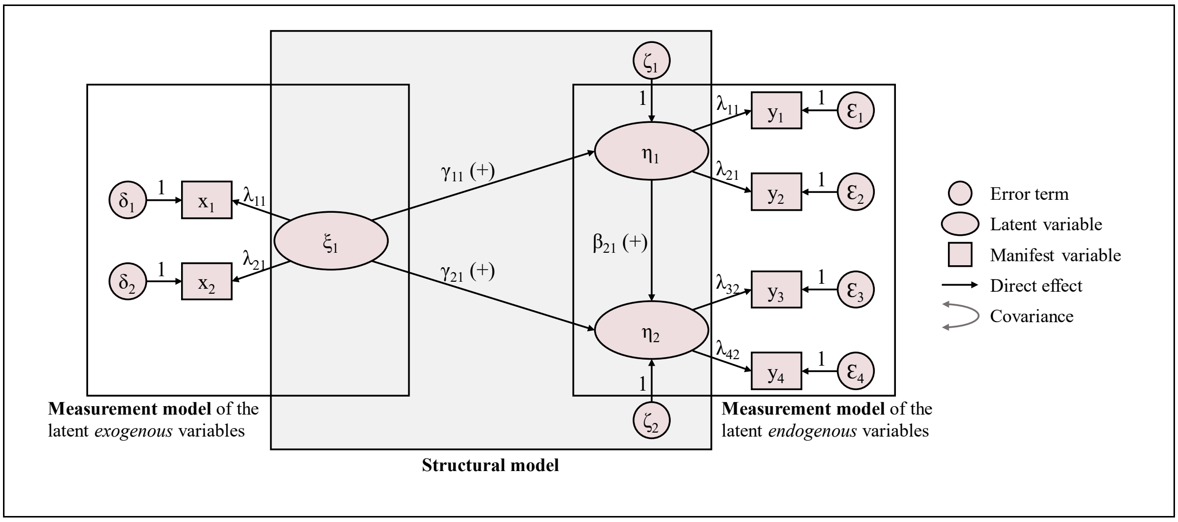
- *Structural model:* The structural model represents the causal relationships between the latent variables postulated ex ante on a theoretical and logical foundation. Therefore, the empirical verification of these causal hypotheses in

[132] It should be noted that a structural equation analysis can also be used for directly observable, i.e., manifest, variables with interrelations. In these cases, the form of a multi-equation system (path analysis) is used.

structural equation analysis has a confirmatory character (Backhaus et al., 2018; Backhaus et al., 2015; Weiber and Mühlhaus, 2014).

- *Measurement model:* In measurement models, the latent variables are operationalized via indicators in order to confirm empirical observations for the variables that cannot be directly observed (Backhaus et al., 2018).

Figure 6.21: Path diagram of an SEM



Source: Own illustration based on Backhaus et al. (2015) and Weiber and Mühlhaus (2014)

For the structural equation analysis composed of the two models described, two approaches are available: the covariance-analytical and the variance-analytical approach (see Figure 6.20). The *covariance-based approach* involves a simultaneous estimation of all parameters of an SEM based on information from the empirical variance-covariance matrix[133] or correlation matrix. The theoretically presumed causal structures can be estimated holistically and tested with inferential statistics (Backhaus et al., 2018; Backhaus et al., 2015; Weiber and Mühlhaus, 2014). In contrast, the *variance-based approach* is based on the least squares estimate and consists of two steps. In the first step, scores for the latent constructs are determined from the empirical measurement data. In the second step, these construct values are employed in a regression analysis to predict the parameters of the structural model (Backhaus et al., 2018; Backhaus et al., 2015; Weiber and Mühlhaus, 2014).

In this thesis, the recommendations made by Weiber and Mühlhaus (2014) are followed. They advise researchers to choose the covariance-analytical approach if, as in

[133] The quadratic and symmetric variance-covariance matrix contains the variances of the manifest variables in the diagonal and the covariances above or below the diagonal (Backhaus et al., 2015).

the present study, "an in-depth theoretically and/or factually substantiated hypothesis system exists" [translated from German] (Weiber and Mühlhaus, 2014, p. 65). They position this methodology as "an approach that considers the totality of variable relationships and is outstandingly suitable for theory evaluation" [translated from German] (Weiber and Mühlhaus, 2014, p. 75). The covariance-analytical approach also has the advantage that both random and systematic measurement errors are explicitly excluded. This avoids the influence of the measurement error variances on the parameter estimates. In contrast, the lack of isolation of the measurement error variance in the variance-analytical approach leads to confounded and thus, often inflationary estimates (Weiber and Mühlhaus, 2014).[134]

In covariance-based SEM, the model parameters are estimated so that the model-theoretical variance-covariance matrix (Σ) reproduces the empirical variance-covariance matrix (S) of the manifest measurement variables as accurately as possible. Consequently, the following discrepancy function shall be minimized:

$$F = (S - \Sigma) \rightarrow min!$$

Where:
S = empirical covariance matrix
Σ = model-theoretical covariance matrix

Various methods are available for estimating the model parameters. In this thesis, the most common estimation method, the maximum likelihood (ML) algorithm, is applied. If a multinormal distribution and a sufficiently large sample are available,[135] inference statistics (χ^2) can be applied to test the null hypothesis that the empirical variance-covariance matrix is equivalent to the model-theoretical variance-covariance matrix. Compared to other estimation approaches, the ML algorithm achieves the most precise estimators (Weiber and Mühlhaus, 2014) because the estimated pa-

[134] For a further differentiation between the two approaches, see Weiber and Mühlhaus (2014).
[135] The normality assumption is validated in Section 6.7.3.3. The critical sample size (N) should be greater than or equal to five times the number of parameters (t) (i.e., $N \geq 5 * t$, see Bagozzi and Yi, 1988) or it should be greater than 50 after subtracting the number of parameters (i.e., $N - t > 50$, see Bagozzi, 1981). Since the number of parameters in the model is 42 (including PE_3) or 40 (after eliminating PE_3, see Section 6.7.3.6), respectively, and the sample size is 270 (see Figure 6.3), both conditions are fulfilled.

rameters and standard errors “are asymptotically unbiased, consistent[,] and efficient” (Schermelleh-Engel, Moosbrugger, and Müller, 2003, p. 26). The ML algorithm aims to minimize the following discrepancy function:

$$F_{ML} = \log|\Sigma| + tr(S * \Sigma^{-1}) - \log|S| - (p + q)$$

Where:
p = number of manifest variables
q = number of parameters to be estimated
tr = trace (sum of the elements on the main diagonal) of a square matrix

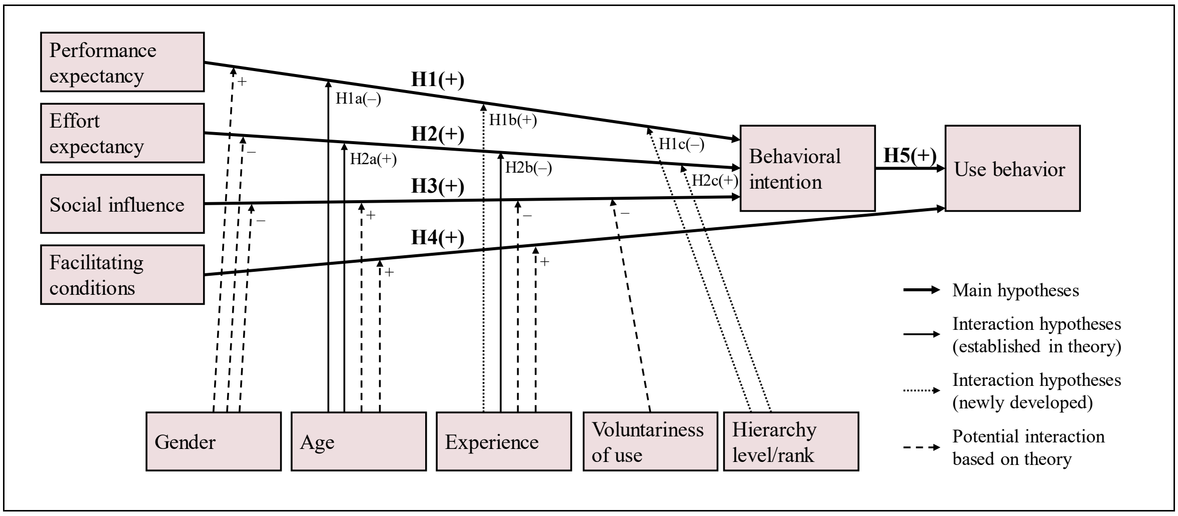
The subsequent validation of the measurement model and the evaluation of the structural model are performed with the statistical software Stata (version 15.1).

6.7.2 UTAUT-based structural equation model on individual adoption

First, the theoretically derived conceptual model, which has been modified based on the findings of the expert interviews (see Sections 5.3.3.1 through 5.3.3.5 and Table 5.6), is briefly reiterated. The five essential relationships of the UTAUT model that will be quantitatively validated in the following sections are confirmed in the interviews in accordance with the theoretical considerations. This relationships are also in accordance with previous studies on analytics adoption in audit firms, except for the social influence construct. It is assumed that performance expectancy (H1), effort expectancy (H2), and the social influence of the environment (H3) have a positive effect on the intention of employees to use data analytics software. The interviews have particularly highlighted the importance of the first two factors. Together with the facilitating conditions (H4), the behavioral intention (H5) is considered to have a positive effect on the actual use of analytics tools in FDD. The predicted relationships between these six constructs are tested by analyzing the model parameters of the basic model. In a second step, the six hypotheses about potential interaction effects (H1a-c, H2a-c) are tested by a multi-group analysis. Interaction effects that are part of the original model developed by Venkatesh et al. (2003), but have not been highlighted by the interviewees, are also validated.

Figure 6.22 summarizes the five main effects as well as the expected role of interaction effects by the variables of gender, age, experience, voluntariness of use, and hierarchy level.[136]

Figure 6.22: Conceptual model on individual adoption including hypotheses



Source: Own illustration

6.7.3 Measurement model

Before the hypotheses can be tested, the measurement model must be validated. In particular, the constructs must be operationalized, the identification of the model ensured, the normality assumption for the ML estimator verified, missing data handled, reliability and validity tested, and the model fit assessed.

6.7.3.1 Operationalization of constructs

Since the hypothetical constructs are not directly observable variables, their theory-based operationalization is subsequently described. The following model is a reflective measurement model, i.e., the causality is shown from construct to item and the measurement error is measured at the level of the individual items (Jarvis, MacKenzie, and Podsakoff, 2003).[137] When selecting indicators, care should be taken to ensure that they reflect the construct as comprehensive as possible (Weiber and Mühlhaus, 2014).

[136] For a reiteration of the differences between the theoretical considerations and expert interview findings concerning the hypothetical interaction effects, see Table 5.6.
[137] See Jarvis et al. (2003) for a distinction between reflective and formative measurement models.

The original UTAUT model by Venkatesh et al. (2003) is largely relied on due to the confirmatory (as opposed to explorative) orientation of the investigation. Modifications of the model during its operationalization take into account the particularities identified in the interviews. This follows the idea set forth by Venkatesh et al. (2003), who state that "measures for UTAUT should be viewed as preliminary and future research should be targeted at more fully developing and validating appropriate scales for each of the constructs with an emphasis on content validity" (p. 468). The variables, including their definitions, measurement scales, and sources, are presented in Table 6.4.

Table 6.4: Adoption of data analytics – Variables definition

Variable	Scale	Source
Actual use (USE): In how many FDD projects do you use data analytics tools instead of traditional solutions?		
USE_1: Frequency in %	0-100	Self-developed based on Compeau, Higgins, and Huff (1999); Thompson et al. (1991)
Behavioral intention (BI): Do you agree with the following statements?		
BI_1: I intend to use data analytics tools in the next FDD projects.	1-7	Taylor and Todd (1995b); Venkatesh et al. (2003)
BI_2: I predict I will use data analytics tools in the next FDD projects.	1-7	Venkatesh et al. (2003)
BI_3: I plan to use data analytics tools in the next FDD projects.	1-7	Venkatesh et al. (2003)
Performance expectancy (PE): Do you agree with the following statements?		
PE_1: Using data analytics tools enables me to accomplish tasks more quickly.	1-7	Davis (1989); Moore and Benbasat (1991); Venkatesh et al. (2003)
PE_2: Using data analytics tools improves the quality of the work I do.	1-7	Davis (1989); Moore and Benbasat (1991)
PE_3: Using data analytics tools I increase my chances of obtaining a promotion and/or raise.	1-7	Compeau et al. (1999); Venkatesh et al. (2003)
Effort expectancy (EE): Do you agree with the following statements?		
EE_1: It is/was easy for me to become skillful at using data analytics tools.	1-7	Davis (1989); Venkatesh et al. (2003)
EE_2: I find data analytics tools easy to use.	1-7	Davis (1989); Venkatesh et al. (2003)
EE_3: Learning to operate data analytics tools is/was easy for me.	1-7	Davis (1989); Moore and Benbasat (1991); Venkatesh et al. (2003)
Social influence (SI): Do you agree with the following statements?		
SI_1: People who are important to me think that I should use data analytics tools.	1-7	Mathieson (1991); Venkatesh et al. (2003); Taylor and Todd (1995b)
SI_2: People in my organization who use data analytics tools have a high profile.	1-7	Moore and Benbasat (1991)
SI_3: The senior management has been helpful in the use of data analytics tools.	1-7	Thompson et al. (1991); Venkatesh et al. (2003)
Facilitating conditions (FC): Do you agree with the following statements?		
FC_1: I have the resources necessary to use data analytics tools.	1-7	Venkatesh et al. (2003)
FC_2: I have the knowledge necessary to use data analytics tools.	1-7	Venkatesh et al. (2003)
FC_3: Data analytics tools are not compatible with other software I use.	1-7	Venkatesh et al. (2003); Taylor and Todd (1995b)

Experience (EXP): How do you assess your current level of experience with different data analytics features?		
EXP_1: Data management (esp. data transformation)	1-7	Self-developed
EXP_2: Descriptive analytics	1-7	Self-developed
EXP_3: Advanced analytics	1-7	Self-developed
EXP_{dummy}[1]	0-1	-
Voluntariness (VOL): Do you agree with the following statements?		
VOL_1: Although it might be helpful, using data analytics tools is certainly not compulsory in my job.	1-7	Moore and Benbasat (1991)
VOL_{dummy}[2]	0-1	-
Hierarchy level/rank (RANK)		
$RANK_{dummy}$[3]	0-1	-
Gender (GDR)		
GDR_{dummy}[4]	0-1	-
Age (AGE)		
AGE_{dummy}[5]	0-1	-

Notes:
The items are adapted to the tense of the verbs, the technology (data analytics software), and the context (FDD). For 7-point rating scales, the value of 1 indicates novice skills (for the experience construct) and strong disagreement (for all other constructs), and the value of 7 indicates expert skills (for the experience construct) and strong agreement (for all other constructs).
1) Following a median split/dichotomization, average response values of EXP_1, EXP_2, and EXP_3 (only when all three survey questions are answered) between 1 and 4 are assigned a value of 0, average response values between 4.01 and 7 are assigned a value of 1.
2) Following a median split/dichotomization, response values between 1 and 3 are assigned a value of 0, response values between 4 and 7 are assigned a value of 1.
3) The consultant, senior consultant, and manager ranks are assigned a value of 0, the senior manager, director, and partner ranks are assigned a value of 1.
4) Females are assigned a value of 0, males are assigned a value of 1.
5) Following a median split/dichotomization, participants aged between 23 and 29 are assigned a value of 0, participants aged between 30 and 66 are assigned a value of 1.

Source: Own illustration

Analogously to Venkatesh et al. (2003), the actual use of analytics software is measured by a single indicator (USE_1). The item reflects the percentage of FDD projects in which respondents use data analytics software. The scale is linearly transformed into a 7-point rating scale due to the large item scale and the correspondingly high variance compared to the other items, which are measured on a 7-point rating scale or as binary dummy variables. Moreover, the error variance of USE_1 is fixed to zero for identification purposes (Weiber and Mühlhaus, 2014).

The behavioral intention construct is measured by the same three indicators (intention, prediction, and planning) used by Venkatesh et al. (2003), who in turn relied on a scale adapted from Davis et al. (1989). As with all other survey questions, the context is adapted to the use of data analytics software and FDD.

In contrast to the operationalization from Venkatesh et al. (2003), the four exogenous latent constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions are represented by three (instead of four) indicators. This approach is intended to keep dropout rates low and to avoid survey fatigue during the response process.

The performance expectancy construct consists of three indicators, one of which is part of the original UTAUT model by Venkatesh et al. (2003) and reflects the efficiency gained through data analytics (PE_1). The second indicator (PE_2) is taken from Davis (1989) and Moore and Benbasat (1991) and reflects quality improvements through software use. The third item (PE_3) combines two previously separate items, promotions and salary increase, from Compeau et al. (1999), which reflect potential career benefits resulting from the use of analytics tools.[138]

The effort expectancy construct consists of three indicators already applied by Venkatesh et al. (2003), which capture the necessary training effort (EE_1 and EE_3) and the ease of use (EE_2).

Building up on findings from the expert interviews, social influence reflects the direct (SI_1) and indirect (SI_2) effects of the social environment as well as the support of the senior management (SI_3). While the study of Venkatesh et al. (2003) contains items SI_1 and SI_3, and thereby captures the concepts of social norms and social factors, this study goes further and also includes aspects of image (SI_2) from Moore and Benbasat (1991).

The fourth exogenous latent construct, facilitating conditions, includes three indicators used by Venkatesh et al. (2003) that reflect the availability of resources (FC_1), the availability of knowledge (FC_2), and the software's compatibility with other systems (FC_3).

To capture the different facets of experience with using data analytics, participants are asked to assess their data management (EXP_1), descriptive analytics (EXP_2), and advanced analytics (EXP_3) skills.

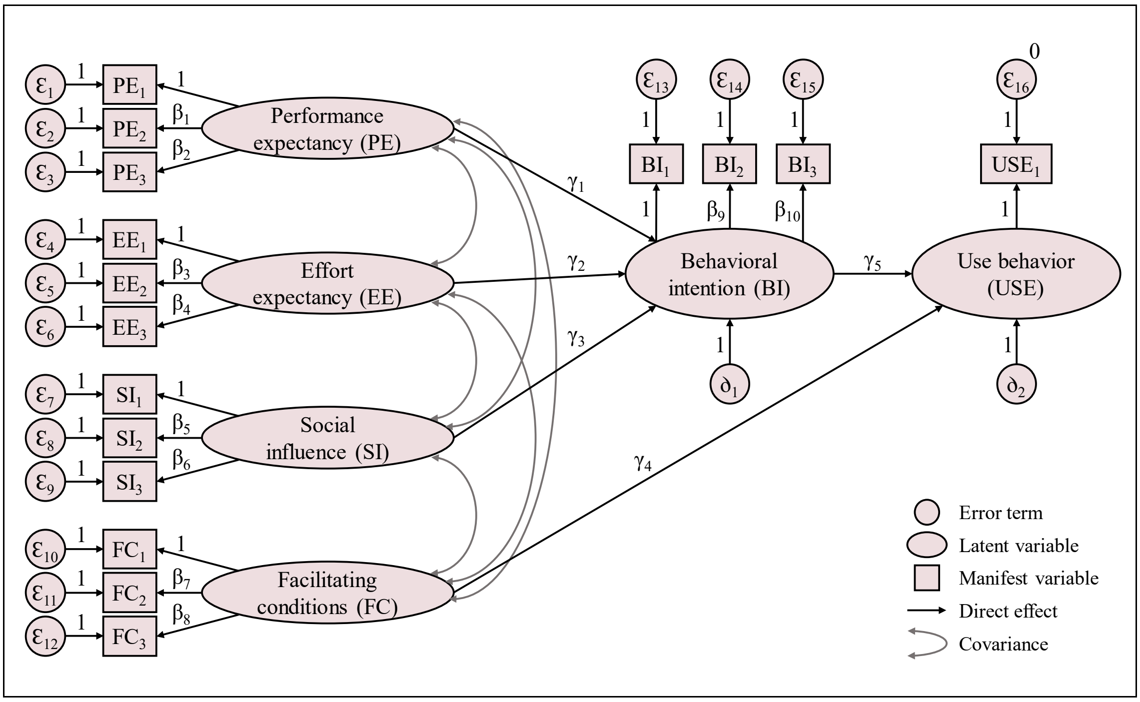
[138] The salary increase aspect is already part of the UTAUT model by Venkatesh et al. (2003), but not combined with the career advancement aspect that was highlighted in the expert interviews.

Building upon the discussion about voluntariness in Footnote 82 (see Section 4.1.3.1), the perceived (instead of actual) voluntariness is queried based on an item developed by Moore and Benbasat (1991).

Finally, demographic information on hierarchy level, gender, and age are examined as binary dummy variables.

The operationalized structural model, in a basic version without interaction effect, is illustrated in Figure 6.23.

Figure 6.23: Operationalized basic model



Source: Own illustration

The path diagram can be transferred into a linear system of equations (Weiber and Mühlhaus, 2014). It contains the following reflective measurement equations:

$$PE_1 = \alpha_1 + PE + \varepsilon_1 \mid PE_2 = \alpha_2 + \beta_1 \cdot PE + \varepsilon_2 \mid PE_3 = \alpha_3 + \beta_2 \cdot PE + \varepsilon_3$$
$$EE_1 = \alpha_4 + EE + \varepsilon_4 \mid EE_2 = \alpha_5 + \beta_3 \cdot EE + \varepsilon_4 \mid EE_3 = \alpha_6 + \beta_4 \cdot EE + \varepsilon_6$$
$$SI_1 = \alpha_7 + SI + \varepsilon_7 \mid SI_2 = \alpha_8 + \beta_5 \cdot I + \varepsilon_8 \mid SI_3 = \alpha_9 + \beta_6 \cdot SI + \varepsilon_9$$
$$FC_1 = \alpha_{10} + FC + \varepsilon_{10} \mid FC_2 = \alpha_{11} + \beta_7 \cdot FC + \varepsilon_{11} \mid FC_3 = \alpha_{12} + \beta_8 \cdot FC + \varepsilon_{12}$$
$$BI_1 = \alpha_{13} + BI + \varepsilon_{13} \mid BI_2 = \alpha_{14} + \beta_9 \cdot BI + \varepsilon_{14} \mid BI_3 = \alpha_{15} + \beta_{10} \cdot BI + \varepsilon_{15}$$
$$USE_1 = \alpha_{16} + USE + \varepsilon_{16} = \alpha_{16} + USE$$

Typically, means and intercepts are considered in multi-group models but not in single-group models (with a single time of measurement) that normally rely on mean-centered variables. In this dissertation, however, they are also applied in the single-group model, because the full information maximum likelihood (FIML) approach is used to replace missing data (see Section 6.7.3.5). The command to perform the FIML approach ("method(mlmv)"), in combination with the command to suppress means and intercepts ("nomeans"), results in the applied statistics program (Stata version 15.1) not displaying fit indices (Aichholzer, 2017). Therefore, the above measurement equations include an intercept (α_i). This, however, has no relevance to the interpretation of the single-group model's results.

The conceptual part consists of two construct equations:

$$BI = \gamma_1 \cdot PE + \gamma_2 \cdot EE + \gamma_3 \cdot SI + \delta_1$$
$$USE = \gamma_4 \cdot BI + \gamma_5 \cdot FC + \delta_2$$

6.7.3.2 Identification of the model

To calculate the model previously outlined, it is necessary that the model is identified (Backhaus et al., 2015). This requires the availability of sufficient empirical information to be able to unequivocally estimate the model parameters. To identify the measurement model, the t-rule[139] must be fulfilled as a necessary condition, which states that the number of model parameters to be estimated must be smaller than (or equal to) the number of observed variances and covariances. Put differently, the degrees of freedom must be greater than (or equal to) zero (Backhaus et al., 2015; Weiber and Mühlhaus, 2014). This is the case in the present model with 94 degrees of freedom.[140] The equations are linearly independent, i.e., the model matrices are positive definite, and thus, meet the sufficient condition (Backhaus et al., 2015;

[139] The t-rule has the following formula:

$$t \leq \frac{1}{2} * (p+q) * (p+q+1) \leftrightarrow df = \frac{1}{2} * (p+q) * (p+q+1) - t \geq 0$$

Where:
t = number of model parameters
p = number of manifest x-indicators
q = number of manifest y-indicators
df = degrees of freedom

[140] In a later step, the item PE_3 is removed from the model (see Section 6.7.3.6). This reduces the number of degrees of freedom to 80.

Weiber and Mühlhaus, 2014). In addition to the measurement model, the structural model is also identified due to its recursive (and not reciprocal) nature and the associated fulfillment of the rank condition.

In addition to the availability of sufficient information, a metric must be defined for the latent variables and the error variables due to their unobservable character (Weiber and Mühlhaus, 2014). For this purpose, one item per latent variable was selected as a reference indicator with a factor loading of 1 (see model equations in Section 6.7.3.1).

6.7.3.3 Data structure and method of estimation

The calculation of SEMs (Kaplan, 2009) and most estimation methods, such as the ML algorithm (Weiber and Mühlhaus, 2014) that is applied in this thesis (see Section 6.7.2), require a normal distribution of the data. Therefore, the data set used is checked for a univariate and multivariate normal distribution based on descriptions by Weiber and Mühlhaus (2014) and Weston and Gore (2006).

Weston and Gore (2006) write that "[t]esting whether the assumptions for multivariate normality are met is impractical as it involves examining an infinite number of linear combinations. One solution is to examine the distribution of each observed variable. This screening for univariate normality can inform researchers whether multivariate normality may be an issue" (p. 735). For this reason, the univariate normal distribution[141] of the data is assessed using the Kolmogorov-Smirnoff test and the Shapiro-Wilk test. The null hypotheses of both tests are rejected if the p-values are less than the chosen alpha level (5% significance level), which is evidence that the data tested is not normally distributed. This applies to all 20 variables in the Kolmogorov-Smirnoff test and to 15 variables in the Shapiro-Wilk test (see Table 6.5). Thus, the results of both tests cast doubt on the normal distribution of the data captured by this survey. However, both tests examine the assumption of a perfect normal distribution, which can lead to the rejection of the null hypotheses even if the values deviate only slightly from the normal distribution. This is especially true in large samples (Hair, Black, Babin, and Anderson, 2010). In addition, the two test methods show certain deficiencies. The Kolmogorov-Smirnoff test is statistically less powerful than

[141] An exactly normally distributed variable has a skewness value and a kurtosis value of zero (Weiber and Mühlhaus, 2014).

the Shapiro-Wilk test (Janssen and Laatz, 2017), while the latter does not work well in samples that contain many identical values, as is the case with rating-scaled survey data.

Table 6.5: Validation of normality assumption – Kolmogorov-Smirnov test and Shapiro-Wilk test

Variable	Kolmogorov-Smirnov test		Shapiro-Wilk test	
	Statistic	Significance	Statistic	Significance
Actual use (USE)				
USE_1[1]	0.096	0.014	0.979	0.000
Behavioral intention (BI)				
BI_1	0.259	0.000	0.934	0.000
BI_2	0.224	0.000	0.929	0.000
BI_3	0.222	0.000	0.928	0.000
Performance expectancy (PE)				
PE_1	0.199	0.000	0.964	0.000
PE_2	0.211	0.000	0.943	0.000
PE_3	0.151	0.000	0.987	0.030
Effort expectancy (EE)				
EE_1	0.148	0.000	0.993	0.292
EE_2	0.150	0.000	0.996	0.764
EE_3	0.154	0.000	0.992	0.183
Social influence (SI)				
SI_1	0.178	0.000	0.961	0.000
SI_2	0.201	0.000	0.974	0.000
SI_3	0.148	0.000	0.988	0.030
Facilitating conditions (FC)				
FC_1	0.170	0.000	0.979	0.001
FC_2	0.152	0.000	0.988	0.023
FC_3[2]	0.228	0.000	0.958	0.000
Experience (EXP)				
EXP_1	0.149	0.000	0.994	0.386
EXP_2	0.141	0.000	0.995	0.504
EXP_3	0.127	0.000	0.980	0.001
Voluntariness (VOL)				
VOL_1	0.139	0.000	0.987	0.017

Notes:
The dummy variables are not displayed.
1) The item was requested on a scale from 0 to 100 and has been linearly transformed to a scale from 1 to 7.
2) The item refers to a negative-wording question and has therefore been reverse-coded.

Source: Own illustration based on survey results

The test for univariate normal distribution can also be performed with the critical ratio (C.R.), which results from the empirically determined skewness and kurtosis coefficients being divided by the corresponding standard error (S.E.). The "moderate conservative interpretation" [translated from German] (Weiber and Mühlhaus, 2014, p. 181) assumes a violation of the normality distribution for C.R. values greater than

2.57 (1% significance level). This criterion is satisfied for 11 of the continuous manifest variables with respect to skewness, but is satisfied for none of the continuous manifest variables with respect to kurtosis (see Table 6.6). Additional criteria to evaluate normality are the absolute values of skewness and kurtosis. From a conservative point of view, normal distribution can be assumed in the interval of [-1; 1] (Temme and Hildebrandt, 2009; Weiber and Mühlhaus, 2014). In the present study, three cases and all 20 cases, respectively, lie outside the interval for skewness and kurtosis, within which normal distribution can be assumed (see Table 23).

Weiber and Mühlhaus (2014) make an important restriction to the normality assumption when rating scales are used:

> [D]ata collected on the basis of rating scales rarely meets the 'strict' test criteria. However, since the distortions […] of the goodness of fit statistics and standard errors of the parameter estimators only occur when there is a significant deviation from the normal distribution, these [test criteria] appear too restrictive in the context of SEM. For this reason, their results are always reported in the literature, but in a subsequent step it is examined whether there is a material violation of the normal distribution assumption. For this purpose, the consideration of skewness and kurtosis measures is used. [translated from German] (p. 181)

A substantial violation of the normal distribution occurs when the skewness and kurtosis coefficients have an absolute value greater than two and seven, respectively (Byrne, 2001; Weiber and Mühlhaus, 2014; West, Finch, and Curran, 1995).[142] Both can be denied in this thesis, since the highest absolute skewness assumes the value 1.152 (for item BI_3) and the highest absolute kurtosis the value 3.968 (for item PE_2) (see Table 6.6). Thus, only a moderate, but not substantial, violation of the normality assumption can be confirmed.[143] Consequently, the ML estimator can be used (Bollen, 1989; Weiber and Mühlhaus, 2014) because it "is robust to moderate violations

[142] Other authors consider higher thresholds appropriate: an absolute amount of three for skewness (Chou and Bentler, 1995), ten for moderate kurtosis, and 20 for extreme kurtosis (Kline, 2015).

[143] Although Weston and Gore (2006) explain that "screening for univariate normality can inform researchers whether multivariate normality may be an issue" (p. 735), an additional test is used to evaluate multivariate normality. Mardia's coefficient, a measure of the multivariate skewness and kurtosis (Mardia, 1970), confirms the previous observation concerning the normality assumption (p=0.0000).

of the normality assumption" (Weston and Gore, 2006, p. 738). The influence of the moderate deviation from the normal distribution is reviewed in Section 6.7.5 using the Satorra-Bentler correction.

Table 6.6: Validation of normality assumption – Skewness and kurtosis

Variable	n	Skewness	Std. error	C.R.	Kurtosis	Std. error	C.R.
Actual use (USE)							
USE_1[1]	270	0.014	0.148	0.094	1.879	0.295	6.360
Behavioral intention (BI)							
BI_1	262	-1.068	0.150	7.098	3.742	0.300	12.480
BI_2	262	-1.112	0.150	7.390	3.805	0.300	12.690
BI_3	263	-1.152	0.150	7.670	3.797	0.299	12.687
Performance expectancy (PE)							
PE_1	262	-0.726	0.150	4.825	2.745	0.300	9.155
PE_2	264	-0.915	0.150	6.104	3.968	0.299	13.283
PE_3	238	-0.403	0.158	2.554	2.203	0.314	7.009
Effort expectancy (EE)							
EE_1	255	-0.330	0.153	2.164	2.478	0.304	8.155
EE_2	254	-0.198	0.153	1.296	2.402	0.304	7.890
EE_3	251	-0.350	0.154	2.277	2.765	0.306	9.030
Social influence (SI)							
SI_1	245	-0.809	0.156	5.201	3.390	0.310	10.940
SI_2	254	-0.648	0.153	4.241	2.647	0.304	8.695
SI_3	255	-0.317	0.153	2.079	2.080	0.304	6.846
Facilitating conditions (FC)							
FC_1	266	-0.549	0.149	3.676	2.389	0.298	8.027
FC_2	266	-0.359	0.149	2.404	2.188	0.298	7.352
FC_3[2]	241	-0.738	0.157	4.706	2.697	0.312	8.634
Experience (EXP)							
EXP_1	266	-0.292	0.149	1.955	2.431	0.298	8.168
EXP_2	262	-0.221	0.150	1.469	2.297	0.300	7.661
EXP_3	259	0.098	0.151	0.648	1.949	0.302	6.464
Voluntariness (VOL)							
VOL_1	264	0.054	0.150	0.360	1.818	0.299	6.086

Notes:

The standard error of skewness is calculated as follows: $SE_{skew} = \sqrt{\frac{6*n*(n-1)}{(n-2)*(n+1)*(n+3)}}$

The standard error of kurtosis is calculated as follows: $SE_{kurtosis} = 2 * SE_{skew} * \sqrt{\frac{n^2-1}{(n-3)*(n+5)}}$

The critical ratio (C.R.) equals the skewness divided by the standard error of skewness and the kurtosis divided by the standard error of kurtosis, respectively.

The dummy variables are not displayed.

1) The item was requested on a scale from 0 to 100 and has been linearly transformed to a scale from 1 to 7.

2) The item refers to a negative-wording question and has therefore been reverse-coded.

Source: Own illustration based on survey results

6.7.3.4 Descriptive statistics

Next, the descriptive statistics of the indicators selected in Section 6.7.3.1 are presented (see Table 6.7). For some variables, inferential statistics in the form of one-tailed Student's t-tests are used to identify institutional and personal differences.

The variable USE_1, whose scale has been linearly transformed from a percentage scale to a 7-point rating scale, has an arithmetic mean of 3.994. This value corresponds to a usage of analytics in 49.9% of FDD projects. In the GSANL region, the average usage rate is 43.5%. This value lies in the interval of 30% to 50% estimated for the German-speaking area by the interviewed experts (see Section 5.3.1). Analytics usage varies considerably and has a standard deviation of 1.731 (or 28.8%, respectively). In addition, statistically significant differences between various demographic and institutional characteristics can be observed. The analytics usage frequency is higher for women ($p=0.0073$), younger consultants ($p=0.0170$), and more junior consultants ($p=0.0628$). It is also significantly higher for employees working for the deals analytics departments ($p=0.0602$), those employed by the Big Four ($p=0.0384$), and those working in the U.S. ($p=0.0000$). The different characteristics correspond to the previous observations from the expert discussions and the questionnaire section concerning the use of analytics.

All three indicators of behavioral intention are at a consistently high level with arithmetic mean values of 5.927 (BI_1), 5.794 (BI_2), and 5.776 (BI_3), respectively, and a median of 6 each. Moreover, these three indicators have the lowest standard deviations out of all items related to the UTAUT.

In contrast, the three indicators used to measure performance expectancy vary in their intensity. While the respondents perceive strong improvements in speed (PE_1; mean: 5.317) and quality of work (PE_2; mean: 5.742), they do not experience equally strong career effects (PE_3; mean: 4.605). The incidence of career benefits resulting from using analytics, such as faster promotions or salary increases, is perceived heterogeneously (32 "n/a" responses; standard deviation: 1.787).

The three indicators for the construct of effort expectancy are at a consistent level of 4.686 (EE_1), 4.496 (EE_2), and 4.665 (EE_3), respectively. This level indicates that the consultants do, in fact, not perceive the training and application of analytics software to be very simple and effortless.

The first two indicators for social influence exhibit mean values of 5.376 (SI_1) and 5.303 (SI_2), indicating that key colleagues serve as role models and that current users typically have a strong profile. The third item that reflects social influence, the support by the senior management (SI_3), has a notably lower mean value of only 4.482. Interestingly, the senior management support is assessed consistently, without significant differences, across demographic characteristics such as age, gender, and hierarchy. However, the helpfulness of the senior management is rated significantly lower for respondents from the transaction services department (p=0.0236), Next Ten companies (p=0.0098), and the GSANL region (p=0.0000). These same respondents also reported lower usage rates (see USE_1 above).

By and large, respondents indicate having the resources (FC_1; mean: 5.041) and knowledge (FC_2; mean: 4.737) necessary for using data analytics tools. Moreover, they do not observe any major difficulties with the compatibility between the analytics software employed and other IT systems (FC_3; mean: 5.278).

The level of experience with different aspects of analytics varies greatly. In particular, expertise in the areas of data management (EXP_1; mean: 4.376) and descriptive analytics (EXP_2; mean: 4.214), which are currently the main fields of application, is much higher than in the area of advanced analytics (EXP_3; mean: 3.417).

Finally, the perceived voluntariness (VOL_1) shows an arithmetic mean of 4.008, which lies almost exactly in the middle between voluntariness and obligation. The high standard deviation of 1.889 indicates strong differences in respondents' perceptions, with few statistically significant personal or institutional differences.[144]

[144] The only statistically significant difference in the VOL_1 variable is observed with respect to the department. Respondents from the deals analytics department perceive the usage of analytics tools as less voluntary than those from the transaction services department (p=0.0415), which appears logical in light of the deals analytics department's positioning as CoE for analytics-related tasks.

Table 6.7: Adoption of data analytics – Summary statistics

Variable	n	Mean	Median	Std. deviation	Min.	Max.
Actual use (USE)						
USE_1[1]	270	3.994	4	1.731	1	7
Behavioral intention (BI)						
BI_1	262	5.927	6	1.228	1	7
BI_2	262	5.794	6	1.340	1	7
BI_3	263	5.776	6	1.387	1	7
Performance expectancy (PE)						
PE_1	262	5.317	6	1.492	1	7
PE_2	264	5.742	6	1.141	1	7
PE_3	238	4.605	5	1.787	1	7
Effort expectancy (EE)						
EE_1	255	4.686	5	1.574	1	7
EE_2	254	4.496	5	1.513	1	7
EE_3	251	4.665	5	1.437	1	7
Social influence (SI)						
SI_1	245	5.376	6	1.408	1	7
SI_2	254	5.303	6	1.447	1	7
SI_3	255	4.482	5	1.781	1	7
Facilitating conditions (FC)						
FC_1	266	5.041	5	1.624	1	7
FC_2	266	4.737	5	1.662	1	7
FC_3[2]	241	5.278	6	1.503	1	7
Experience (EXP)						
EXP_1	266	4.376	4	1.593	1	7
EXP_2	262	4.214	4	1.649	1	7
EXP_3	259	3.417	3	1.690	1	7
EXP_{dummy}[3]	258	0.461	0	0.499	0	1
Voluntariness (VOL)						
VOL_1	264	4.008	4	1.889	1	7
VOL_{dummy}[4]	264	0.564	1	0.497	0	1
Hierarchy level/rank (RANK)						
$RANK_{dummy}$[5]	265	0.332	0	0.472	0	1
Gender (GDR)						
GDR_{dummy}[6]	262	0.767	1	0.423	0	1
Age (AGE)						
AGE_{dummy}[7]	248	0.540	1	0.499	0	1

Notes:
1) The item was requested on a scale from 0 to 100 and has been linearly transformed to a scale from 1 to 7.
2) The item refers to a negative-wording question and has therefore been reverse-coded.
3) Following a median split/dichotomization, average response values of EXP_1, EXP_2, and EXP_3 (only when all three survey questions are answered) between 1 and 4 are assigned a value of 0, average response values between 4.01 and 7 are assigned a value of 1.
4) Following a median split/dichotomization, response values between 1 and 3 are assigned a value of 0, response values between 4 and 7 are assigned a value of 1.
5) The consultant, senior consultant, and manager ranks are assigned a value of 0, the senior manager, director, and partner ranks are assigned a value of 1.
6) Females are assigned a value of 0, males are assigned a value of 1.
7) Following a median split/dichotomization, participants aged between 23 and 29 are assigned a value of 0, participants aged between 30 and 66 are assigned a value of 1.

Source: Own illustration based on survey results

6.7.3.5 Handling of missing data

When reviewing the summary statistics in Table 6.7, it becomes evident that the number of observations varies for the different items. This can be explained by the fact that SEMs are particularly susceptible to missing data. This is because the use of multiple indicators is associated with the higher likelihood that a respondent has missed a value for at least one variable. The handling of missing data is "of particular importance in the application of SEMs, since the [structural equation analysis] requires the existence of a complete data matrix" [translated from German] (Weiber and Mühlhaus, 2014, p. 175).

In this study, 188 out of 270 respondents completed the entire questionnaire section on adoption related to the basic model.[145] Put differently, 82 respondents selected the "n/a" option for at least one survey question, as all questions in this section were marked as mandatory.[146] Overall, 4.9% of the data is missing for the basic model and 4.4% for the entire model, including moderator variables.[147] The item non-response does not show a focus on individual items when omitting the rating.

Since there is no evidence of systematic bias due to missing values, the FIML estimate is used to account for missing values (Arbuckle, 1996). The FIML technique is characterized by replacing missing values directly in the parameter estimation of the model (Weiber and Mühlhaus, 2014). In contrast to traditional, less complex methods such as listwise or pairwise deletion or mean substitution, the FIML technique neither reduces the sample nor distorts the true distribution, variances, correlations, and standard errors. Moreover, it leads to a low proportion of convergence failures and small type 1 error rates (Enders and Bandalos, 2001).

[145] The basic model refers to Figure 6.23, i.e., it does not take into account moderating variables.
[146] Without missing values for item PE_3, which is subsequently eliminated (see Section 6.7.3.6), 201 out of 270 questionnaires do not contain any missing data.
[147] After eliminating the indicator PE_3 from the model (see Section 6.7.3.6), 4.4% and 4.0% of the data is missing.

6.7.3.6 Reliability and construct validity

Before the empirical evaluation of the SEM, the quality of the reflective measurement models must be checked on the basis of their reliability[148] and validity[149] (Weiber and Mühlhaus, 2014).

Reliability is examined at the item level using the corrected item-total correlation.[150] Indicators are identified that contribute little to the construct measurement and are eliminated from the analysis to improve the internal consistency of a construct. Bortz and Döring (2006) refer to previous scientific literature and posit that "positive values between 0.3 and 0.5 [can be regarded as] mediocre and values greater than 0.5 [are] good" [translated from German] (p. 220). In this study, all items pass the lower threshold for internal consistency of 0.3 and 11 out of 15 items also surpass the threshold of 0.5 (see Table 6.8). However, the PE_3 indicator is eliminated as its corrected item-total correlation of 0.3096 is considered borderline. Eliminating this indicator substantially improves the Cronbach's alpha value of the associated performance expectancy construct from 0.6164 to 0.7270.

Internal consistency is evaluated at the construct level using the aforementioned Cronbach's alpha. Ursachi, Horodnic, and Zait (2015) outline the "general[ly] accepted rule […] that [an alpha] of 0.6[151]-0.7[152] indicates an acceptable level of reliability, and 0.8 or greater a very good level" (p. 681). Alpha values greater than 0.95, however, are an indication of redundancy (Hulin, Netemeyer, and Cudeck, 2001). All alpha values for the latent constructs lie within the acceptable range: Social influence (a broadly defined construct) receives the lowest (unstandardized) Cronbach's alpha value (0.6759) and behavioral intention (a narrowly defined construct) receives the

[148] Reliability is defined as "accuracy of a measurement instrument" [translated from German] (Weiber and Mühlhaus, 2014, p. 128) and requires the absence of random error.
[149] Validity is defined as "the extent to which a measurement instrument also measures what it should measure" [translated from German] (Weiber and Mühlhaus, 2014, p. 128 and 156) and requires not only the absence of random error, but also of systematic error.
[150] In contrast to the item-total correlation, the calculation of the corrected item-total correlation excludes the considered variable and thus improves the quality of the result, especially for a small number of indicators as is the case in this thesis (Weiber and Mühlhaus, 2014).
[151] See e.g., Bagozzi and Yi (1988) and Hair et al. (2010).
[152] See e.g., Bollen (1989) and Krafft, Götz, and Liehr-Gobbers (2005).

highest value (0.9365) (see Table 6.8).[153] Overall, the Cronbach's alpha values suggest a good reliability of the measurement models.

Table 6.8: Validation of reliability – Corrected item-total correlation and Cronbach's alpha

Variable	Corrected item-total correlation	Cronbach's alpha (standardized)
Performance expectancy (PE) before exclusion of PE_3		
PE_1	0.4619	0.6164 (0.6581)
PE_2	0.5643	
PE_3	0.3096	
Performance expectancy (PE) after exclusion of PE_3		
PE_1	0.5911	0.7270 (0.7437)
PE_2	0.5911	
Effort expectancy (EE)		
EE_1	0.8542	0.9340 (0.9367)
EE_2	0.8670	
EE_3	0.8867	
Social influence (SI)		
SI_1	0.5862	0.6759 (0.6979)
SI_2	0.4491	
SI_3	0.4021	
Facilitating conditions (FC)		
FC_1	0.7473	0.8342 (0.8411)
FC_2	0.6949	
FC_3	0.6707	
Behavioral intention (BI)		
BI_1	0.8599	0.9365 (0.9402)
BI_2	0.8844	
BI_3	0.8718	

Notes:
The actual use (USE) construct is not displayed as it represents a single-indicator latent variable for which the error variance is artificially fixed to zero for model identification purposes (i.e., it technically equals a manifest variable).
Cronbach's alpha is calculated as follows: $\alpha = \frac{K}{K-1} * (1 - \frac{\sum_{i=1}^{K} var(Y_i)}{var(X)})$ with $X = \sum_{i=1}^{K} Y_i$

Variables definition:
$var(Y_i)$ = variance of indicator i
$var(X)$ = variance of the observed total test scores
K = number of indicators

Source: Own illustration based on survey results

However, corrected item-total correlation and Cronbach's alpha rely on restrictive assumptions and do not take measurement error into account (Weiber and Mühlhaus, 2014). Therefore, a third measure is employed to assess reliability: the composite

[153] Given that the constructs consist of a maximum of three items, the lower threshold (0.6) is considered appropriate for Cronbach's alpha in this thesis, as the value is "strongly dependent on the number of indicators used" [translated from German] (Weiber and Mühlhaus, 2014, p. 137).

reliability (CR) (Raykov, 1997). This measure stems from confirmatory factor analysis and is similar to Cronbach's alpha from exploratory factor analysis. Values greater than 0.6 indicate internal consistency of the scale items (Bagozzi and Yi, 1988). In this thesis, all constructs surpass this threshold with social influence having the lowest value (0.766) and behavioral intention having the highest value (0.940) (see Table 6.9).

In addition to CR, a criterion that is often examined for reliability is the average variance extracted (AVE). It indicates the percentage of variance of the latent construct explained by its indicators. Fornell and Larcker (1981) require at least half of the variance to be explained by the constructs' items, i.e., a cutoff value of 0.5. All latent variables, except for social influence,[154] surpass the critical value (see Table 6.9).

Table 6.9: Validation of reliability – Average variance extracted and composite reliability

Constructs	Average variance extracted (AVE)	Composite reliability (CR)
Performance expectancy (PE)[1]	0.601	0.768
Effort expectancy (EE)	0.836	0.925
Social influence (SI)	0.479	0.766
Facilitating conditions (FC)	0.606	0.777
Behavioral intention (BI)	0.840	0.940

Notes:
1) The values for the performance expectancy (PE) construct are calculated after elimination of the PE_3 indicator.
The actual use (USE) construct is not displayed as it represents a single-indicator latent variable for which the error variance is artificially fixed to zero for model identification purposes (i.e., it technically equals a manifest variable).
The AVE is calculated as follows: $AVE = \frac{\sum_{i=1}^{K} \lambda_i^2}{\sum_{i=1}^{K} \lambda_i^2 + \sum_{i=1}^{K} var(\delta_i)}$
The CR is calculated as follows: $CR = \frac{\left(\sum_{i=1}^{K} \lambda_i\right)^2}{\left(\sum_{i=1}^{K} \lambda_i\right)^2 + \sum_{i=1}^{K} var(\delta_i)}$

Variables definition:
λ_i = standardized loading for the i^th^ indicator
$var(\delta_i)$ = variance of the error term for the i^th^ indicator
K = number of indicators

Source: Own illustration based on survey results

Overall, the measurement model can be considered reliable since the critical thresholds for corrected item-total correlation, Cronbach's alpha, CR, and AVE are surpassed.

[154] Since the social influence construct is only marginally below the critical value for the AVE and exceeds the thresholds of all other reliability measures, a reliable measurement can also be assumed for this construct.

The confirmation of reliability serves as the necessary condition for the assessment of the validity of the measurement. Consequently, the next step is to examine content and construct validity (Weiber and Mühlhaus, 2014).[155]

Content validity can be assumed to be given due to the underlying theoretical foundation of the constructs, the establishment of the items in numerous studies, and the examination of the questionnaire with experts in a pre-test (Weiber and Mühlhaus, 2014). It is therefore assumed that "the surveyed indicators of a construct represent the content semantic area of the construct and that the measured items reflect all defined contents of a construct" [translated from German] (Weiber and Mühlhaus, 2014, p. 157).

Construct validity, which consists of nomological, convergent, and discriminant validity, "exists if the measurement of a construct is not falsified by other constructs or systematic errors" [translated from German] (Weiber and Mühlhaus, 2014, p. 159).

Nomological validity, i.e., the theoretical foundation of the relationships between the constructs, is considered given (Weiber and Mühlhaus, 2014). The causal hypotheses of the structural model are derived from Venkatesh et al.'s (2003) UTAUT model and the expected interaction effects are slightly modified based on the expert interviews. The selection of the indicators is also based on theoretical considerations, which have already been empirically validated in previous adoption studies. The goodness of fit indices of the SEM (see Section 6.7.3.7) confirm the nomological validity of the causal relationships (Weiber and Mühlhaus, 2014).

Convergent validity, i.e., the measurements equality of a construct captured by two maximally different methods, is difficult to examine in economic and social sciences. In particular, two maximally different measuring methods are rarely present and are associated with considerable effort (Weiber and Mühlhaus, 2014). Fornell and Larcker (1981) explain that in research practice for the verification of convergent (and also discriminatory) validity, the measurement of multiple items for a construct (with the same method) has established itself instead of the application of maximally different methods. They therefore advise verifying whether the threshold value of 0.5

[155] A third type of validity, criterion validity, can only be tested for through the comparison with valid external criteria, which are not present in this study (Weiber and Mühlhaus, 2014).

of the AVE is exceeded, which is an indication of the presence of convergent validity (Fornell and Larcker, 1981). AVE has already been calculated to assess the internal consistency (see Table 6.9). Therefore, in addition to reliability, convergent validity can also be assumed for the measurement model.

Discriminant validity ensures a construct's empirical uniqueness. This means that constructs shall represent phenomena of interest, which must not be captured by other measures in the model (Hair et al., 2010). In order to assess discriminant validity, research has traditionally focused on the Fornell-Larcker criterion[156] (Fornell and Larcker, 1981) and the examination of cross-loadings[157] (Chin, 1998b). However, Henseler et al. (2015) demonstrate in a Monte Carlo simulation study that these approaches "have an unacceptably low sensitivity" (p. 128) and "do not reliably detect the lack of discriminant validity in common research situations" (p. 115). They propose an alternative measure: the heterotrait-monotrait ratio of correlations (HTMT), which is "a comparison of the heterotrait-heteromethod correlations and the monotrait-heteromethod correlations" (Henseler et al., 2015, p. 128).[158] More specifically, the average of the heterotrait-heteromethod is divided by the geometrical mean of two constructs' average monotrait-heteromethod correlation. Since the HTMT is an estimate of the correlation between two constructs, a value of zero indicates no relationship whereas a value of one indicates a perfect correlation. Discriminant validity is ensured for values below the thresholds of 0.85 (Clark and Watson, 1995; Kline, 2015) or 0.90 (Gold, Malhotra, and Segars, 2001; Teo, Srivastava, and Jiang, 2008). In this study, all but one HTMT are well below both threshold values (see Table 6.10). The HTMT value for the constructs of behavioral intention and social influence (0.85) meets the first, conservative threshold, but is well below the second, more liberal threshold. Consequently, discriminant validity is established in this study.

[156] According to the Fornell-Larcker criterion, "discriminant validity is established if a latent variable accounts for more variance in its associated indicator variables than it shares with other constructs in the same model. To satisfy this requirement, each construct's average variance extracted (AVE) must be compared with its squared correlations with other constructs in the model." (Henseler, Ringle, and Sarstedt, 2015, p. 116).

[157] According to the examination of cross-loadings, which is grounded in exploratory factor analysis, "discriminant validity is shown when each measurement item correlates weakly with all other constructs except for the one to which it is theoretically associated" (Gefen and Straub, 2005, p. 92).

[158] The authors explain that "HTMT builds on the available measures and data and – contrary to the standard MTMM [multitrait-multimethod] approach – does not require simultaneous surveying of the same theoretical concept with alternative measurement approaches" (Henseler et al., 2015, p. 121) This is considered difficult and is associated with high efforts (Weiber and Mühlhaus, 2014).

Table 6.10: Validation of discriminant validity – Heterotrait-monotrait ratio of correlations

Latent constructs	PE[1]	EE	SI	FC	BI	USE
Performance expectancy (PE)[1]	–					
Effort expectancy (EE)	0.65	–				
Social influence (SI)	0.74	0.66	–			
Facilitating conditions (FC)	0.55	0.70	0.75	–		
Behavioral intention (BI)	0.74	0.61	0.85	0.67	–	
Actual use (USE)	0.64	0.52	0.59	0.48	0.60	–

Notes:
1) The values for the PE construct are calculated after the elimination of the item PE_3.

The HTMT is calculated as follows: $HTMT_{ij} = \dfrac{\frac{1}{K_i * K_j} * \sum_{g=1}^{K_i} \sum_{h=1}^{K_j} r_{ig,jh}}{\sqrt{\frac{2}{K_i * (K_i - 1)} * \sum_{g=1}^{K_i - 1} \sum_{h=g+1}^{K_i} r_{ig,ih} * \frac{2}{K_j * (K_j - 1)} * \sum_{g=1}^{K_j - 1} \sum_{h=g+1}^{K_j} r_{jg,jh}}}$

Variables definition:
K_i = number of indicators of construct i (the same holds for construct j)
$r_{ig,ih}$ = correlation between indicator g of construct i and indicator h of construct i (the same holds for construct j)

Source: Own illustration based on survey results

Overall, content validity and construct validity, i.e., nomological, convergent and discriminant validity, can be assumed for the model.[159] The model fit statistics are examined in the following.

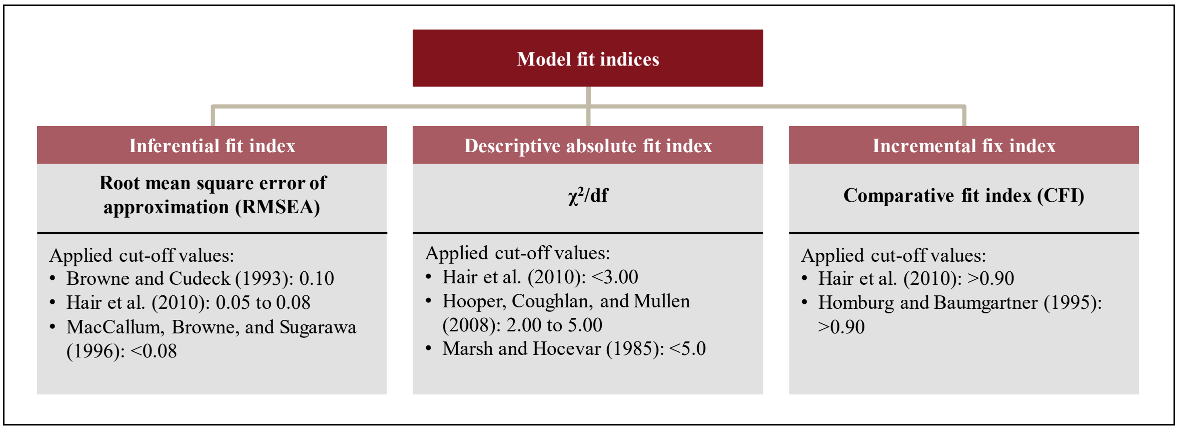
6.7.3.7 Assessment of the model fit

When assessing the overall model, it is important to initially check for implausible results (so-called Heywood cases, such as negative variances, communalities >1, or correlations >1) (Aichholzer, 2017; Backhaus et al., 2015; Weiber and Mühlhaus, 2014). These can be excluded in this thesis, so that the parameter matrices are positively definite.

In the next step, the model fit can be assessed using various inferential, descriptive, and incremental fit indices (Weiber and Mühlhaus, 2014). Model fit is the congruence between the variances and covariances calculated using the parameter estimator and the empirically obtained variances and covariances. In the following, fit measures from all three areas are considered in order to reflect different aspects of the model fit and obtain meaningful test statistics (see Figure 6.24).

[159] The reliable and valid parameter estimates of the measurement model are illustrated in Table A.5 (unstandardized) and Table A.6 (standardized) in the appendix.

Figure 6.24: Model fit indices



Source: Own illustration based on Weiber and Mühlhaus (2014)

The χ^2 test or likelihood ratio test is an important inferential statistical fit measure. It tests the null hypothesis that the model-theoretical variance-covariance matrix is equal to the empirical variance-covariance matrix, i.e., that the residual matrix is equal to zero. However, the test's strict requirements (e.g., multivariate normality of the variables, large sample size) and the inherent assumption that the unknown population covariance matrix and the estimated sample covariance matrix correspond exactly are rarely fulfilled in practice. For this reason, two variants have been established to provide a better approximation. First, the χ^2 value can be regarded as a descriptive measure. In this case, the ratio between the χ^2 and the degrees of freedom should not exceed the threshold values of 3 (Hair et al., 2010) or 5 (Hooper, Coughlan, and Mullen, 2008; Marsh and Hocevar, 1985). Smaller values indicate a better model fit. Second, the root mean square error of approximation (RMSEA) index represents an alternative measure, which examines the discrepancy per degree of freedom. It tests "whether a model can approximate reality well" [translated from German] (Weiber and Mühlhaus, 2014, pp. 204–205) and not whether it is the correct representation of the sample variance-covariance matrix. The RMSEA should not exceed the value of 0.1 (Browne and Cudeck, 1993) or, for a stricter interpretation, 0.08 (Hair et al., 2010; MacCallum, Browne, and Sugawara, 1996). Besides these two criteria, the comparative fit index (CFI) as an incremental fit index is also employed. It builds on a baseline comparison between the empirically obtained model and the independence model, i.e., the model with the worst fit. Concretely, the CFI indicates to what extent the two models deviate from the minimum value of the discrepancy function while taking distribution distortions into account (Weiber and Mühlhaus, 2014). CFI values above the threshold of 0.9 indicate a good model fit (Hair et al., 2010; Homburg and Baumgartner, 1995). In their review of 41 publications, McDonald and

Ho (2002) note that the most frequently reported fit indices are χ^2, CFI, and RMSEA, reinforcing the academic relevance of the indices used in this dissertation.[160]

Table 6.11 summarizes the empirically observed values of the three indices. The value of 2.721 for χ^2/df is clearly below the cutoff value (5) and the value of 0.952 for CFI is clearly above the threshold (0.9). Only the value of 0.080 for RMSEA exceeds the less strict threshold (0.10); but lies at, not below, the stricter threshold (0.08). Overall, a good model fit can be concluded, confirming that the model is properly developed.

Table 6.11: Assessment of the model fit – RMSEA, χ^2/df, and CFI

Criterion	Category	Value
RMSEA	Inferential fit index	0.080
χ^2/df	Absolute descriptive fit index	2.721[1]
CFI	Incremental fit index	0.952

Notes:
1) The χ^2 value equals 217.70 with 80 df.
The RMSEA is calculated as follows: $RMSEA = \sqrt{\max(\frac{\chi^2 - df}{df*(N-g)}; 0)}$
The CFI is calculated as follows: $CFI = 1 - \frac{\max(\hat{C} - df; 0)}{\max(\hat{C}_b - df; 0)}$

Variables definition:
χ^2 = chi-squared of the formulated model
df = degrees of freedom
N = sample size
g = number of groups (normally, g=1)
C = minimum of the discrepancy function of the formulated model
C_b = minimum of the discrepancy function of the independence model

Source: Own illustration based on survey results

In the following, the possible improvement of the model fit by adding paths is examined by means of the Lagrange multipliers. The value 49.054, by far the highest modification index value, would suggest adding a correlation between the error terms of the indicator variables FC_1 and FC_3.[161] However, the already well-fitting model is not

[160] χ^2 is reported in 41 studies, CFI is reported in 21 studies, and RMSEA is reported in 20 studies (McDonald and Ho, 2002).
[161] Adding the correlation of the error terms of FC_1 and FC_3 to the model leads to a negative variance of the error term of FC_2, i.e., an implausible result that is conceptually impossible. Thus, a phantom variable can be included to impose a constraint that forces the variance of the error term of FC_2 to be greater than or equal to zero. While the inclusion of the correlated error terms would be technically possible, it would lead to conceptual issues.

modified because there is no substantive, theoretically sound explanation for correlated error terms (Hermida, 2015).

6.7.4 Structural model

In a final evaluation step, the parameter estimates of the valid, reliable, and well-fitting model can be compared with the hypotheses postulated in Sections 5.3.3.1 through 5.3.3.5, enabling an interpretation of the results. A multi-group analysis also serves to test the hypotheses regarding interaction effects.

6.7.4.1 Parameter estimates

Before evaluating the structural relationships between the latent constructs of the UTAUT model, the explanatory power of the model is considered. Following a classification set forth by Chin (1998b),[162] the explained portion of the endogenous constructs can be evaluated as substantial for behavioral intention with an R^2 value of 0.77 and as moderate for the actual use with an R^2 value of 0.40 (see Figure 6.25). However, a comparison to R^2 values from studies investigating a similar context is more meaningful than an orientation towards these threshold values. It is evident that the declared proportion of variance of the two endogenous latent variables is (almost) at the same level as in the original UTAUT study by Venkatesh et al. (2003) (R^2 for behavioral intention: 0.77; R^2 for actual use: 0.52), and thereby well above results from other technology adoption theories "that routinely explain over 40 percent of the variance in individual intention to use technology" (Venkatesh et al., 2003, p. 426). Moreover, a considerably larger portion of the variance of behavioral intention can be explained than in the 27 previous quantitative studies, which also employ the UTAUT model, as investigated in the meta-analysis by Dwivedi et al. (2011) (average R^2 for behavioral intention: 0.39).

To validate the key hypotheses (H1 to H5), the sign, magnitude, and significance levels of the structural path coefficients are examined. Since the unstandardized parameter estimates must be considered in the context of the scale applied, the standardized parameter estimates are used for interpretation (Weiber and Mühlhaus, 2014). The standardized path coefficients have values between -1 and +1. A value near these poles indicates a very strong relationship between the constructs, whereas values

[162] When evaluating the proportion of the explained variance, many researchers follow Chin (1998b), who regards the R^2 values obtained in his own study of 0.19 as weak, 0.33 as moderate, and 0.67 as substantial.

close to 0 do not suggest a relationship (Hair, Hult, Ringle, and Sarstedt, 2014). Standardized coefficients greater than |0.2| are considered meaningful (Chin, 1998a).

The model results illustrated in Figure 6.25 are briefly presented below.[163] A detailed discussion and the derived implications are given in Chapter 7. The discussion includes the comparison between findings from past research and the qualitative analysis within this thesis.

In the present dissertation, the relationships postulated in H1, H3, H4, and H5 are significant with positive standardized parameters above 0.2. H2, in contrast, cannot be supported.

In line with H1, performance expectancy positively influences behavioral intention at the 1% significance level with a standardized path coefficient of 0.28. After eliminating PE_3 from the model, the construct was measured by improvements of both the efficiency (PE_1) and the effectiveness (PE_2) of the respondents' work. Consequently, the perception of these benefits results in a higher willingness to use analytics software.

Contrary to theoretical considerations and findings from the expert interviews, the model does not support the presumed effect of effort expectancy on behavioral intention (H2). Put differently, the effort respondents must make to become proficient in using data analytics tools does not discourage them from using such tools. Thus, this result contradicts the expert evaluations in which this factor was emphasized as an essential driver for the adoption of analytics. Interestingly, Dwivedi et al.'s (2011) meta-analysis also finds that the impact of effort expectancy is lowest among the different constructs; however, effort expectancy was still found to have a statistically significant influence. The results of the meta-analysis by Williams et al. (2015) support this view and find that the construct has a significantly positive influence in only 64 of the 110 studies (58%) that quantitatively examine this factor.

As posited by H3, the social influence construct positively affects behavioral intention at the 0.1% significance level with a very high path coefficient of 0.64. The

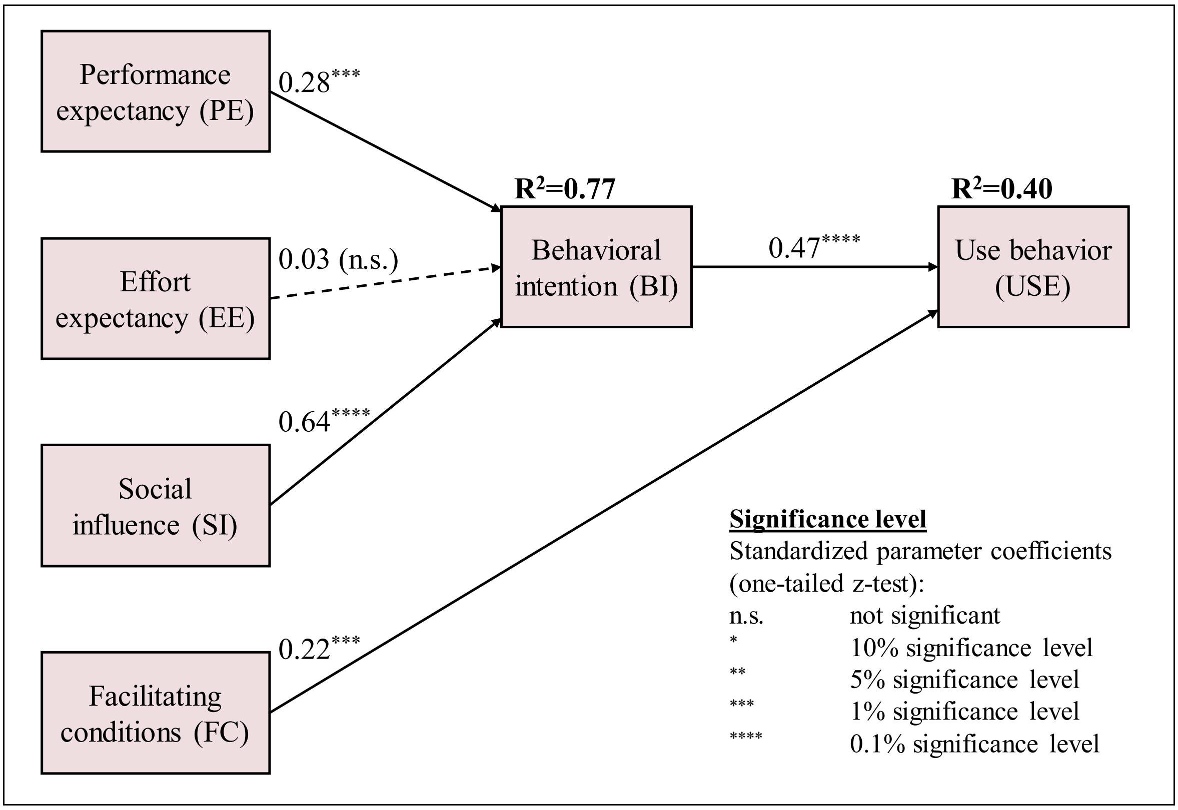
[163] A tabular overview of the standardized parameter estimates of the structural model can be found in Table A.7 in the appendix.

highly significant impact of the social influence construct can be traced back to the early stage of the adoption process. It is during this phase that the factor primarily has its effect (see Section 4.1.3.2). Compared to the other constructs, it has the highest influence on the individuals' intentions to use analytics tools. Interestingly, the relative importance of this factor has not been highlighted in the expert discussions. By contrast, the interviewees assign more weight to performance expectancy and effort expectancy (see Section 5.3.3).

In line with theoretical considerations, the actual usage is influenced by facilitating conditions (H4) with a standardized path coefficient of 0.22 (1% significance level). Consequently, the existence of appropriate organizational and technical infrastructure directly affects the use of analytics.

Finally, behavioral intention (H5) has the expected positive effect on the actual usage with a standardized path coefficient of 0.47 (0.1% significance level).

Figure 6.25: Structural model – Standardized parameter estimates



Source: Own illustration

The results of the hypothesis tests of the main effects of the structural model are summarized in Table 6.12.

Table 6.12: Validation of hypotheses on main effects

Hypotheses	Validation
Effects on behavioral intention (BI)	
H1: The influence of *performance expectancy* on behavioral intention is positive.	Supported
H2: The influence of *effort expectancy* on behavioral intention is positive.	Rejected
H3: The influence of *social influence* on behavioral intention is positive.	Supported
Effects on actual use (USE)	
H4: The influence of *facilitating conditions* on actual usage is positive.	Supported
H5: The influence of *behavioral intention* on actual usage is positive.	Supported

Source: Own illustration

Finally, after having observed multiple statistically significant differences between the GSANL region and the U.S. in Section 6.6.1 et seqq., is appears appropriate to control the above results for country-specific effects. Consequently, the SEM is tested only for the GSANL in order to exclude possible distortions caused by the answers from the U.S.-based employees with a greater affinity for technology.[164] The results are comparable in terms of sign, magnitude, and significance levels (see Table A.8 in the appendix). Consequently, the findings described above are valid not only for the entire survey sample, but also for respondents from the GSANL region.[165]

6.7.4.2 Multi-group analysis of interaction effects

After testing the main effects of the UTAUT model, the expected moderation effects are validated. Therefore, unlike most of the papers that use the UTAUT model that have examined only the main effects (Venkatesh, Thong, and Xu, 2016), this study aims to provide a comprehensive and accurate overview of individual adoption.

An interaction occurs when the effect of an explanatory variable on a dependent variable, i.e., its strength and/or direction, is influenced by a third term, the moderator variable (Hopwood, 2007; Weiber and Mühlhaus, 2014). The effects of moderators on relationships between latent constructs can be analyzed with different approaches.

[164] The GSANL subsample includes 201 observations, i.e., 60 observations from U.S.-based respondents and nine observations of respondents who did not report their country of employment are eliminated.

[165] Note that the subsequent multi-group analysis to test potential interaction effects cannot be conducted for the GSANL subsample because the group models with a released parallel slopes assumption (and the minimization of their discrepancy functions, respectively) could not be calculated by Stata v15.1.

A multi-group analysis is conducted by taking into account the manifest, mostly categorical variables, the focus on pure (and not quasi) interaction effects, and the given sample size (Huber, Heitmann, and Herrmann, 2006; Weiber and Mühlhaus, 2014). For this purpose, each moderator variable is divided into two groups, as the sample size of 270 observations prevents a larger differentiation. For the same reason, only two-way interactions are examined. The interaction term GDR_{dummy} is binary in nature. The moderator variables AGE_{dummy}, $RANK_{dummy}$, VOL_{dummy}, and EXP_{dummy} have already been dichotomized in earlier parts of this thesis (see Table 6.7 for the summary statistics).[166]

The following multi-group analysis consists of two steps. First, equivalence of the measurement models of the two groups is examined by comparing an unconstrained model for both groups with a model in which measurement constraints are imposed (Schumacker and Lomax, 2010; Weiber and Mühlhaus, 2014). A nested model is constructed if measurement equivalence is confirmed by a likelihood ratio test or if the goodness of fit indices do not considerably improve through the relaxation of equality constraints. Measurement equality constrains are imposed, i.e., the intercepts and coefficients of the measurement models of both group are assumed to be equal. In the second step, the construct equations are tested for potential factor mean differences and differences in the regression coefficients of the potentially moderated main effect across the two groups. For this purpose, two further models are compared. The first model contains measurement equality constraints as well as equality constraints to the structural coefficients (so-called parallel slopes assumption). For the second model, the parallel slopes assumption is relaxed for the structural coefficient of the variable under investigation. Schumacker and Lomax (2010) refer to these models as "intercept only and intercept-slope models" (p. 318). Subsequently, a likelihood ratio test is used to examine whether significant differences between the models exist.

Potential interaction effects are tested for each moderator (gender, age, hierarchy level, voluntariness, and experience) on four main effects (PE, EE, SI on BI and FC

[166] The transformation of a continuous variable when artificially constructing a categorical variable for the purpose of defining a group inevitably leads to a loss of information (Schumacker and Lomax, 2010).

on USE). Thus, not only the hypothesized interaction effects (H1a-c, H2a-c),[167] but also theoretically established moderations, which were not directly supported in the expert interviews, illustrated with dotted lines in Figure 6.22 are validated.

However, only one hypothetical interaction effect (see Table 6.13) and one theoretically plausible interaction effect (see Table 6.14) are statistically significant.[168]

Table 6.13: Validation of hypotheses on interaction effects

Hypotheses	Validation
Effects of performance expectancy (PE) on behavioral intention (BI)	
H1a: The influence of performance expectancy on behavioral intention is moderated by *hierarchy level*, such that the effect will be stronger for more junior employees (except partners).	Rejected[1]
H1b: The influence of performance expectancy on behavioral intention is moderated by *age*, such that the effect will be stronger for younger employees.	Rejected
H1c: The influence of performance expectancy on behavioral intention is moderated by *experience*, such that the effect will be stronger for employees with more analytics experience.	Rejected
Effects of effort expectancy (EE) on behavioral intention (BI)	
H2a: The influence of effort expectancy on behavioral intention is moderated by *hierarchy level*, such that the effect will be stronger for more senior employees.	Rejected
H2b: The influence of effort expectancy on behavioral intention is moderated by *age*, such that the effect will be stronger for older employees.	Rejected
H2c: The influence of effort expectancy on behavioral intention is moderated by *experience*, such that the effect will be stronger for employees with less analytics experience.	Supported

Notes:
1) Since partners were excluded from the group of more senior employees based on findings from the qualitative analysis, the hypothesis is tested with three different dummy variables. First, the established $RANK_{dummy}$ variable that distinguishes between junior and senior employees, without specifically accounting for partners, is tested. Second, a new dummy variable is created, which eliminates the observations of partners. Third, another new dummy variable is created, which assigns the value of 0 to partners, and thereby assumes that their perceptions are similar to those of more junior employees. For none of the variants is a significant moderating effect of the hierarchy level observed.

Source: Own illustration

[167] Note that hypotheses H2a-c are examined even though the main effect of effort expectancy on behavioral intention is not statistically significant. This investigation is necessary because, as in the case of cross-over effects, significant interactions can occur while the main effect is not significant.

[168] The detailed results of the multi-group analysis, which tests (i) hypothetical interaction effects, (ii) theoretically established interaction effects, and (iii) potential further, though not empirically established, interaction effects are shown in Table A.9, Table A.10, Table A.11, Table A.12, Table A.13, Table A.14, and Table A.15 in the appendix.

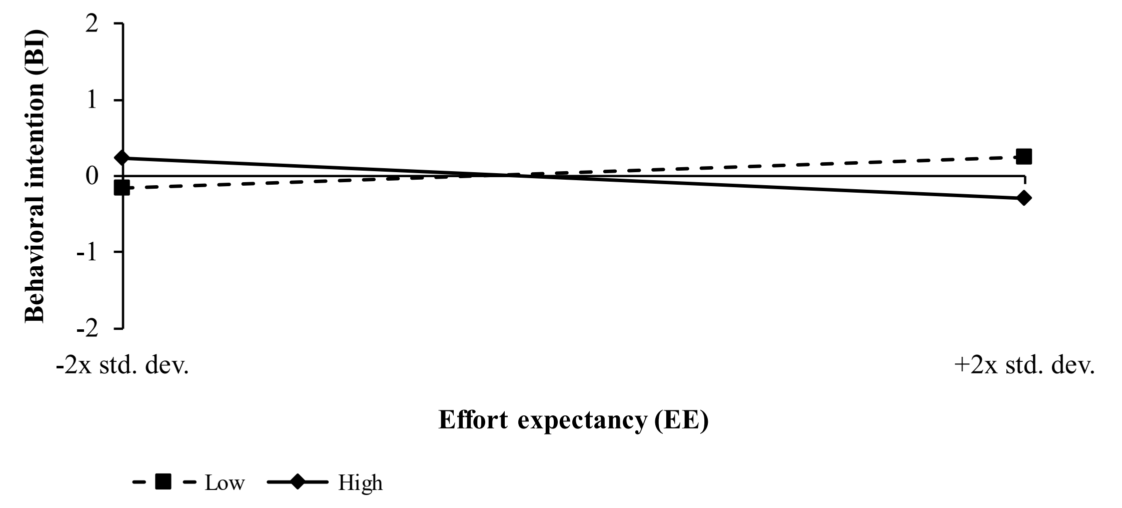
Table 6.14: Validation of theoretical considerations on interaction effects

Theoretical considerations	Validation
Effects of performance expectancy (PE) on behavioral intention (BI)	
The influence of performance expectancy on behavioral intention is moderated by *gender*, such that the effect will be stronger for men.	Rejected
Effects of effort expectancy (EE) on behavioral intention (BI)	
The influence of effort expectancy on behavioral intention is moderated by *gender*, such that the effect will be stronger for women.	Rejected
Effects of social influence (SI) on behavioral intention (BI)	
The influence of social influence on behavioral intention is moderated by *gender*, such that the effect will be stronger for women.	Rejected (reverse effect)
The influence of social influence on behavioral intention is moderated by *age*, such that the effect will be stronger for older employees.	Rejected
The influence of social influence on behavioral intention is moderated by *experience*, such that the effect will be stronger for employees with less analytics experience.	Rejected
The influence of social influence on behavioral intention is moderated by *voluntariness*, such that the effect will be stronger under conditions of less voluntary use.	Rejected
Effects of facilitating conditions (FC) on actual use (USE)	
The influence of facilitating conditions on actual usage is moderated by *age*, such that the effect will be stronger for older employees.	Rejected
The influence of facilitating conditions on actual usage is moderated by *experience*, such that the effect will be stronger for employees with more analytics experience.	Rejected

Source: Own illustration

In the following, the two statistically significant interaction effects are presented. First, the effect of effort expectancy on behavioral intention is positively increasing for FDD consultants with a low level of experience and negatively increasing for those with a high level of previous experience. However, employees with less previous experience have a significantly lower level of effort expectancy. Figure 6.26 illustrates the cross-over interaction, which is significant on a 5%-level (p=0.0443) (see Table A.15). The interaction effect is in line with the expert assessments from the interviews, the theoretical considerations made by Venkatesh et al. (2003), and the findings from past finance and accounting research (Mahzah and Lymer, 2014). It can be interpreted as follows: For consultants with a high level of experience, the impact of effort expectancy on their behavioral intention is negative. These experienced consultants may find it more galvanizing to participate in more in-depth learning and if operating the software was more difficult (i.e., effort expectancy was lower). In brief, highly experienced consultants may appreciate more difficult trainings and use cases. The opposite holds true for less experienced consultants. They appreciate a high level of effort expectancy, which in turn leads to a more positive increase in behavioral intention. Consequently, a high level of comfort in the training and execution of analytics software use is necessary to foster the behavioral intention to use analytics software for the group of less experienced consultants. The different behavior indicates the need to specifically address both groups, which is discussed in Section 7.3.

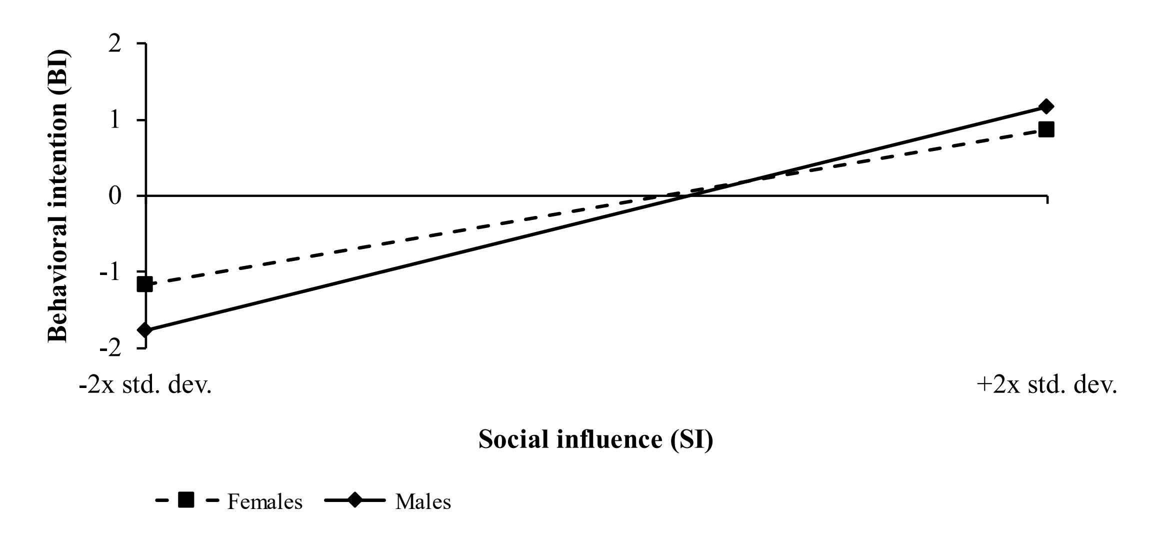
Figure 6.26: Interaction effect of experience on the EE-BI relationship



Source: Own illustration

Second, the effect of social influence on behavioral intention is more positively increasing for men (see Figure 6.27). Interestingly, the interaction effect of gender, which is significant on a 10%-level (p=0.0940) (see Table A.9), contradicts previous empirical findings, which observe a more positive effect for women (Venkatesh et al., 2003). Of note, the overall level of social influence is significantly higher for women even though its impact on behavioral intention is lower (see Table A.9). Consequently, social influence is a stronger driver of behavioral intention for men, but it is on average significantly higher for women. It follows that addressing the relatively weaker social perception of men provides a strong lever to increase adoption.

Figure 6.27: Interaction effect of gender on the SI-BI relationship



Source: Own illustration

6.7.5 Robustness testing via Satorra-Bentler correction

Satorra and Bentler's (1994) scaled test statistics are applied in order to test the robustness of results with respect to the moderate violation of the normal distribution assumption (see Section 6.7.3.3). An estimated multiplicative correction factor is used to modify the test statistics for misspecifications of the normality assumption in such a way that their distribution approaches the χ^2 distribution.

Since Stata (version 15.1) does not allow for combining the Satorra-Bentler correction with the FIML estimation to handle missing data, only 201 (see Section 6.7.3.5) instead of 270 observations are analyzed.[169] Therefore, the values without the Satorra-Bentler correction (see Table 6.15) deviate slightly from the values obtain for the full sample reported in Section 6.7.3.7 (see Table 6.11). The χ^2/df ratio of 2.225 is similar to the ratio obtained without correction for nonnormality (2.467). The values of RMSEA (0.078 vs. 0.085) and CFI (0.948 vs. 0.945) are also similar for the sample of 201 observations. Therefore, as outlined in Section 6.7.3.3, the ML estimator can be used although there is a moderate violation of the normality assumption.

[169] Curran, West, and Finch (1996) demonstrate that the Satorra-Bentler correction performs well across all sample sizes tested (with a minimum sample size of 100). Consequently, the forced reduction of the sample size, since missing data is excluded, does not cause any bias.

Table 6.15: Assessment of the model fit – RMSEA, χ^2/df, and CFI after Satorra-Bentler correction

Criterion	Category	Value before correction	Value after correction
RMSEA	Inferential fit index	0.085	0.078
χ^2/df	Absolute descriptive fit index	2.467[1]	2.225[2]
CFI	Incremental fit index	0.945	0.948

Notes:
1) The χ^2 value equals 197.36 with 80 df.
2) The χ^2 value equals 178.03 with 80 df.

The RMSEA is calculated as follows: $RMSEA = \sqrt{\max(\frac{\chi^2-df}{df*(N-g)};0)}$

The CFI is calculated as follows: $CFI = 1 - \frac{\max(\hat{C}-df;0)}{\max(\hat{C}_b-df;0)}$

Variables definition:
χ^2 = chi-squared of the formulated model
df = degrees of freedom
N = sample size
g = number of groups (normally, g=1)
C = minimum of the discrepancy function of the formulated model
C_b = minimum of the discrepancy function of the independence model

Source: Own illustration based on survey results

6.7.6 Summary

Section 6.7 deals with the adoption of data analytics technology by individual FDD consultants from leading audit firms. A modified UTAUT model, which is based on theoretical considerations as well as expert assessments, is tested through covariance-based SEM.

Before evaluating the model results, the latent constructs are operationalized, identification of the measurement model and the structural model is ensured (t-rule, positive definite matrix, recursiveness, rank condition), the sample size is assessed, and missing data is replaced (FIML). The normality assumption is also validated (Kolmogorov-Smirnov test, Shapiro-Wilk test, C.R., absolute skewness and kurtosis, Satorra-Bentler correction). Additionally, reliability (corrected item-total correlation, Cronbach's alpha, AVE, CR), as well as content and construct validity, i.e., nomological, convergent (AVE), and discriminant validity (HTMT), are tested for. Finally, the model fit is evaluated (RMSEA, χ^2/df, CFI). Overall, the high goodness of fit is the result of the thorough development of the model, including the incorporation of findings from expert interviews and the completion of a subsequent extensive review of the model. Consequently, the model is well-suited to provide insights on (i) the level of adoption (research question 3) and (ii) the factors that affect individual adoption (research question 4).

Overall, (i) the average level of adoption has reached 49.9% among the respondents, i.e., analytics is used in every second FDD project. For the GSANL region, the average usage rate of 43.5% corresponds to the interval indicated in the expert interviews (30-50%). Interestingly, the use of analytics varies considerably. Employees report high levels of experience in data management and descriptive analytics, however, they are less experienced in advanced analytics. This gap supports the view outlined by the experts interviewed and underscores that the current focus of analytics usage lies on the basic functions (see Section 5.3.1). Demographic differences (higher usage for women, younger, and more junior consultants) and institutional disparities (higher usage for Big Four firms, deals analytics departments, and in the U.S.) can also be observed. First, these findings suggest that the use of analytics at the *individual level* is still lagging behind among men, as well as older, more senior professionals. While the latter development is in line with the observations from the expert interviews, the greater reluctance to use analytics among men was not highlighted in the qualitative analysis. Second, the results reveal that the use of analytics at the *organizational level* is significantly lower in the Next Ten firms and in the GSANL region. This finding is in line with the experts' assessments of company size as a decisive factor. Consequently, the Next Ten, which are smaller than the Big Four, and the GSANL-based organizations, which are smaller than the U.S.-based organizations, suffer from the expected structural disadvantages to adoption (e.g., in terms of personal and financial resources). Finally, the lower degree of technology utilization by the transaction services department compared to the deals analytics department arises because the latter is a specifically analytics-oriented organization.

Besides identifying differences in usage rates across demographic and institutional groups, (ii) the decisive factors affecting the use of analytics tools at the personal level are also identified. For this purpose, the modified UTAUT model is applied. The model exhibits a high explanatory power, as demonstrated by the R^2 values of 0.77 for behavioral intention and 0.40 for actual use, thus outperforming earlier adoption theories. The model is clearly well-suited to shedding light on the factors that (directly and indirectly) influence the use of analytics. The structural coefficients and the multi-group analysis of interaction effects reveal interesting findings of great value for both research and managerial practice.

While the 20 experts interviewed assumed that performance expectancy and effort expectancy are the key decision-making criteria for individuals, the quantitative analysis of 270 survey responses paints a different picture. By far the most crucial factor is social influence, i.e., the influence of important others. This is especially true for men, since the effect is moderated by gender. Consequently, social aspects offer the greatest levers for audit firms to increase behavioral intention, and thereby increase the use of analytics. Respondents broadly agree that key colleagues serve as role models and that current users have a strong profile. This appears plausible, especially since both perceptions are strengthened by existing analytics champion programs (see Section 5.3.3.3). One aspect of the social influence factor that lags behind the others points towards an avenue for improvement: senior management support. For example, it has already been described in the expert discussions that the partnership has a high level of awareness for the use of analytics and promotes its use; however, the partnership also struggles with prioritizing long-term profits (requiring prior investments into technology and education) over short-term profits, which can thereby inhibit adoption due to conflicting financial incentives. In addition, the role of directors and senior managers is often seen as critical (see Section 5.3.2.2). Leadership endorsement appears to be especially weak in Next Ten firms, the transaction services department, and the GSANL region. In contrast, the assessment of leadership endorsement does not significantly differ across demographic groups. Potential measures to promote social influence in general, and executive support in particular, are discussed in Section 7.3.

As anticipated, performance expectancy is a driver of behavioral intention. Professionals who more positively perceive the improvements in time (efficiency) and quality (effectiveness), possess a more assertive attitude towards using analytics.[170]

Surprisingly, effort expectancy, which is emphasized by the experts interviewed as the most important determinant of individual adoption (see Section 5.3.3.2), does not have a significant influence at all. One reason is that the effect is cancelled out between different groups. More concretely, a cross-over interaction effect can be observed for the experience variable with a positive effect of effort expectancy for less

[170] The aspect of career benefits (e.g., promotion or salary increase) through the use of analytics tools could not be considered in the structural equation analysis, because the corresponding item had to be eliminated from the model due to its low corrected item-total correlation.

experienced consultants and a negative effect of effort expectancy for the more experienced consultants. This finding indicates that more experienced employees could be further stimulated to employ analytics tools through more difficult trainings and tasks, while the opposite holds true for less experienced consultants. Overall, the strong discrepancy between the assessment of the more technology-oriented interview partners and the sample representative of the overall population, i.e., also the less analytically inclined employees, shows how perceptions are different in both groups. The implications are discussed in Section 7.3.

Facilitating conditions and behavioral intention have the expected direct and positive influence on the use of analytics. The largest room for improvement, in terms of supporting conditions, are identified in the area of knowledge. This area simultaneously has the highest impact out of the three items of the construct. Potential approaches for audit firms are outlined in Section 7.3.

Finally, despite the regional differences in the usage behavior identified, the findings concerning the adoption of analytics are valid not only for the entire sample but also the GSANL subsample.

The impact of the individual adoption factors and moderator variables on theoretical considerations, in the literature on analytics in the field of auditing, in the expert interviews, and finally in the questionnaire is summarized in Table 6.16.

Table 6.16: Comparison of individual adoption factors for analytics in audit firms (2/2)

UTAUT core constructs	Direct and moderating effects	Expected and observed relationship with adoption			
		UTAUT	Audit analytics literature	Interviews	Questionnaire
Performance expectancy[1]	**Direct**	+	+	+	+
	Gender[2]	+		?[4]	none
	Age	–		–	none
	Experience	none		+	none
	Hierarchy level	not tested		–	none
Effort expectancy[1]	**Direct**	+	+	+	none
	Gender[2]	–		?[4]	none
	Age	+		+	none
	Experience	–	–	–	–
	Hierarchy level	not tested		+	none
Social influence[1]	**Direct**	+	none	+	+
	Gender[2]	–		?[4]	+
	Age	+		?[5]	none
	Voluntariness[3]	–		?[5]	none
	Experience	–		?[5]	none
Facilitating conditions	**Direct**	+	+	+	+
	Age	+		?[4]	none
	Experience	+		?[6]	none
Behavioral intention	**Direct**	+	+	+	+

Notes:
1) The effect of performance expectancy, effort expectancy, and social influence is measured on behavioral intention and not on actual use behavior.
2) A "+" sign indicates that the effect is stronger for men; a "–" sign indicates that the effect is stronger for women.
3) A "+" sign indicates that the effect is stronger for voluntary settings; a "–" sign indicates that the effect is stronger for mandatory settings.
4) Based on the qualitative analysis, no prediction, if any, can be made about the effect of gender.
5) Based on the qualitative analysis, no prediction, if any, can be made about the effect of age, voluntariness, and experience in the context of social influence.
6) Based on the qualitative analysis, no prediction, if any, can be made about the effect of experience in the context of facilitating conditions.
Three-way interactions are not depicted in this table.

Source: Own illustration

7 Discussion, implications, and conclusion

First, this chapter discusses the research design, including both its strengths and limitations (Section 7.1). Next, key empirical findings are summarized and discussed in 19 brief statements (Section 7.2). Finally, the chapter concludes with the presentation of implications for managerial practice (Section 7.3) and research (Section 7.4).

7.1 Discussion of the research design

Thus far, previous literature in the finance and accounting domain that is concerned with the topics of big data and data analytics has been confined to only four genealogies, eminently limited in its extent, predominantly conceptual in its orientation, and vague in its assertions. This dissertation is intended to establish a fifth, hitherto largely neglected but highly relevant research area with respect to the topics of big data and data analytics: FDD. Four research questions related to *use* and *adoption* are examined. In doing so, this thesis responds the numerous calls for practice-oriented research. The review of a broad spectrum of theoretical, conceptual studies and the few empirical observations from adjacent literature streams, especially auditing, form the basis for investigating the use dimension from a process-oriented view and the adoption dimension from a technology adoption theory view. The subsequent mixed methods research builds on this theoretical foundation. In particular, this approach allows for the identification of disparities between adjacent literature streams and the field of FDD (see Section 7.4).

In this thesis, the mixed methods research design is particularly applicable as the research problem requires simultaneously an interpretative understanding and quantification. Indeed, this approach supports the objectives of triangulation, expansion, and development. The initial qualitative analysis takes a primarily inductive perspective: Guided expert interviews serve to explore the use of analytics and develop hypotheses about the adoption of analytics. Building on this, the subsequent quantitative analysis of data obtained from a structured online questionnaire allows earlier results to be generalized (or contested) and the hypotheses to be validated.

The research in this thesis benefits greatly from this mixed methods research design. First and foremost, rare first-hand insights into a sensitive and timely topic could be gained from a great number of practitioners from the Big Four and Next Ten firms (20 interview partners; 333 survey respondents). This data is well representative of the market for FDD services and therefore allows for the identification of differences across various demographic and institutional dimensions. This aspect is of particular importance, as the due diligence literature to date has mainly been written by practitioners, who tend to take a company-specific, not universally applicable perspective. Second, the qualitative analysis impresses in both depth and breadth. In particular, the diversity of interview partners (regarding department and hierarchical level) and the length of the interviews (with an average duration of more than one hour) allow for the in-depth coverage of a broad research scope. Third, the subsequent quantification of observed phenomena, which is essentially missing in previous literature, allows for highly robust findings. In contrast to most previous adoption studies, the structural equation analysis also tests interaction effects via a multi-group analysis. Moreover, the impressively high explanatory power of the SEM (R^2 values of 0.77 for behavioral intention and 0.40 for actual use) outperforms prior adoption research.

Despite its numerous advantages, the limitations of the selected research design and methodology must also be considered. First, the majority of interview partners can be characterized as having an above-average affinity for analytics technology. One the one hand, this selection of interview partners is necessary to explore how analytics are used in the FDD process. On the other hand, it limits the representativeness and consequently the generalizability of the qualitative analysis findings. Therefore, the use of two different methodologies is essential. The quantitative analysis reveals different assessments made by the experts and by the large survey sample (e.g., in the perception of the effort expectancy factor). In particular, the survey sample is largely representative (i.e., only slightly skewed towards juniority) and is likely not to suffer from self-selection bias. Second, the necessary degree of observation comparability is achieved with the cross-sectional research design by conducting all interviews and the questionnaire in less than seven months. However, developments over time (e.g., to further investigate the proposed trends or to examine potential changes in critical factors at different stages of adoption) can only be captured in longitudinal research, which could consequently extend this study. Third, the study of adoption relies on self-reported usage (Williams et al., 2015), which is one of the most common limitations in studies using the UTAUT (Dwivedi et al., 2011). However, no other method is available to obtain such data. Even if usage data were collected by companies at the individual level, it would certainly be treated with utmost confidentiality and would not be shared. Finally, as extensively discussed in Section 6.7.3.3, the results of the structural equation analysis must be interpreted in light of a moderate, but not substantial, violation of the normality assumption. The impact of this limitation is considered to be minimal because (i) survey data obtained from rating scales is commonly not normally distributed and (ii) the Satorra-Bentler correction clearly reveals that data model fit does not suffer from this circumstance (see Section 6.7.5).

7.2 Discussion of empirical findings

In the following paragraphs, the main findings related to each of the four research questions are summarized and discussed in 19 brief statements.

Research question 1: Use of (big) data sources

1. **In recent years, data availability, granularity, standardization, quality, and access in FDD have improved significantly.** In the past, these aspects constituted limiting factors, especially on the buy-side and for small and medium-sized, owner-managed targets. In recent years, in conjunction with technological progress, starting with the introduction of virtual data rooms, an increase of data availability and data granularity (in terms of both time and content) has been observed. Consequently, investors have adjusted their expectations upwards and sellers – especially in exclusivity situations – increasingly provide such data for de-risking purposes (i.e., avoid losing the interest of bidders or acquiescing to purchase price discounts). Despite the improvements, sellers in German-speaking countries are more data-sensitive and restrictive compared to the U.S. market.
2. **Data availability, as key enabler and driver of analytics, is particularly high in sell-side deals with large, data-driven target firms held by financial sponsors.** High data availability and granularity, primarily from target-internal sources, facilitate (*enabler*) or even necessitate (*driver*) the application of analytics tools in FDD. The main determinant of data availability is (i) the initiator. In the GSANL region, the gap between sell-side and buy-side engagements is particularly large, suggesting more restrictive sellers in these countries. Additional significant factors include (ii) the size of the target company, (iii) its owner (financial vs. strategic investor), and (iv) its data culture. By contrast, (v) the exclusivity of negotiations, (vi) the target firm's structure (public vs. private with financial owner vs. private with family owner), and (vii) the fragmentation of the sales portfolio are less decisive parameters.

3. **Although financial information from target companies remains the primary source of FDD, external sources and non-financial information are increasingly being integrated.** In particular, the usage figures of non-financial information are remarkable: 97.6% (88.2%) of respondents have already employed internal (external) non-financial data in FDD. Such data is primarily employed in the profitability analysis – predominantly in conjunction with financial data. In line with adjacent finance and accounting research, non-financial data supports the analysis of previously inaccurately measured or unmeasured items (e.g., intangible off-balance sheet assets such as the customer base) and thus strengthens the certainty of investment decisions. Despite their beneficial integration into FDD and the high level of experience mentioned above, the experts indicate that external non-financial data is currently used in only approximately one in ten transactions. Based on their use in the analytics-inclined U.S. firms, a further increase in the inclusion of external sources can also be expected in the GSANL region going forward.
4. **The evermore frequent use of target-internal and target-external non-financial data underscore the increasing commercial orientation of FDD.** Direct access to the target companies' IT systems enables the extraction of non-financial information. This data is primarily used to supplement financial analyses, especially of the EBITDA because of its frequent use in various valuation approaches. The contemporary focus is on customer and product data, while production and supply chain-related information is used less often. This distinction illustrates FDD's increasing focus on commercial analyses. Analyses of the cost situation, which are equally important for the profitability situation, are still subordinately important. This finding can be confirmed for the inclusion of external non-financial data (mainly transactional/market, demographic, and website data). Finally, in contrast to adjacent finance and accounting research, social media data is rarely exploited and unstructured data (e.g., audio, image, and video data), whose analysis is more complex and time-consuming, is not used at all.
5. **The majority of data used in FDD is *big* – but not in all dimensions.** From the consultants' points of view, the data sets used are big in terms of volume; this is especially true for traditional accounting and financial data, which is often available at transaction level. However, target-internal data is neither generated at a high velocity (no real-time data) nor does it vary greatly in its structure (mostly structured data). The less frequently used types of target-external data exhibit greater variety (more semi-structured data) but are not generated at high velocity

either. Hence, the sheer volume drives the imperative to introduce analytics tools with advanced storage and processing capabilities.

6. **Data requests and data verification, adapted to the new conditions, affect the preparation phase of FDD.** First, broadened access to target-internal data leads to fewer, but more specific, data requests and questions. As a result, less management involvement is required and a higher process speed can be attained. Second, it is no longer feasible to analyze all existing data, as has previously been the case. Time constraints typical of M&A transactions necessitate the diligent selection of the *right* data for subsequent analyses. This change prompts earlier discussions with the management teams of the target companies. Third, in addition to checking completeness, verifying data quality becomes increasingly important – especially for externally extracted data sources.

Research question 2: Use of data analytics

7. **The primary use of data management and descriptive analytics software supports process efficiency, but a gradual shift towards insight and value-orientation is expected.** The principal use of (mostly commercial off-the-shelf) data management and descriptive analytics tools in the current, early stage of adoption underscores the contemporary focus: enhancing process efficiency through increasing standardization, partial automation, and offshoring. In contrast, the acquisition of additional insights by leveraging the advanced features that analytics solutions offer when compared to traditional tools is currently a by-product rather than a focus. However, as adoption increases and consultants progressively become more skilled, audit firms are expected to gradually shift to a stronger emphasis on (i) gaining insight and (ii) strengthening value creation. While the former objective arises due to the additional functions offered by analytics solutions, the latter is also caused by external market conditions (high cash reserves/dry powder, high price pressure). Accordingly, a greater use of visualization techniques and predictive analytics is expected in the future.
8. **The development of a comprehensive data model increases the lead time in the preparation phase, but is necessary to harness subsequent benefits.** A comprehensive data model, which serves as the *single version of the truth*, lays the foundation to subsequently take advantage of analytics. The benefits encompass not only higher process efficiency (e.g., standardization, partial automation, rapid integration of updates, fast response to ad hoc requests), but also improved

quality of results (e.g., through increased data quality and transparency, performance of previously unused analyses, increased flexibility, deeper insights). Thus, analytics ultimately supports all three objectives of FDD. However, essential steps in the development of the data model are still mostly manual effort, which causes an increased lead time in the preparation phase. Moreover, interim results for prioritized parts of the deal scope cannot be discussed by audit firms and their clients.

9. **A newly emerging, project-specific cost-benefit trade-off must be considered when deciding whether or not to apply analytics solutions.** For projects that do neither necessitate nor prevent the use of analytics due to extremely high or low data availability, respectively, a cost-benefit trade-off arises: The efficiency-related benefits of analytics need to justify the additional lead time required for data preparation. The decisive factors relate to (i) the deal and target itself, (ii) the project setting, and (iii) the data situation. Besides data availability, the most crucial determinants of the trade-off are the scope and complexity of the transaction. These factors are followed, by a wide margin, by time constraints (especially in the GSANL region) and by budget constraints (especially for Next Ten firms).
10. **The profitability analysis, especially commercial analyses, is the focus area of the current application of analytics.** Profitability analysis as the primary field of application benefits from (i) the advanced functionalities of analytics software (e.g., reconciliations, data compilation in carve-out deals) and (ii) the ability to analyze larger, more granular data sets (e.g., price-volume and constant currency analysis). In line with the increasing focus on value levers, and fueled by high data granularity, analyses with a commercial focus provide especially fruitful soil for the use of analytics (e.g., price-volume, customer churn, and cohort analysis).
11. **In the other three review areas, analytics is used to a lesser extent; nonetheless, promising applications can be anticipated for the future.** Balance sheet analysis particularly benefits from the mapping logic (provision of the net asset format) and visualization techniques (detection of anomalies requiring normalization). In cash flow analysis and business plan validation, there are currently few use cases for analytics. There are three underlying causes for this lower applicability. First, FDD often focuses on profitability analysis due to the frequently applied earnings multiples and accruals-based valuation techniques (especially for SMEs). Second, these areas suffer from lower data quality (balance sheet analysis), availability (cash flow analysis), and granularity (business plan validation). Third, FCF is usually determined using an indirect approach, a statement that is

only valid for cash flow analysis. Nonetheless, multiple auspicious use cases in these areas are being considered for the future (e.g., machine-learning based classification, predictive analytics-based development of an alternative business plan).

12. **Interactive dashboard visualizations already facilitate management discussions and are expected to prospectively supplement the final FDD report.** Dashboard solutions, which are already employed to facilitate management discussions, are very likely to supplement final FDD reports in the foreseeable future, especially in those reports executed by Big Four firms. Before this will be possible, essential technological features must be developed to fulfill two critical prerequisites. First, server-based dashboards must allow various analyses to be performed without accessing the underlying data. This will alleviate concerns that the selling party may have regarding sharing its data with bidders, especially competitors. Second, the creation of a frozen status must occur to meet the needs of banks and insurance companies that rely on the static nature of the due diligence report for risk management and liability reasons.
13. **Prospectively, service providers may need to redefine their business models to adapt to the changed conditions.** One the one hand, the increase in automation and offshoring lowers audit firms' costs. One other hand, these aspects jeopardize the growth potential of the revenue base under the traditional bill-by-hour pricing. Improved efficiency does not substantiate an increase in the number of man days and fierce competition does not allow audit firms to charge considerably higher prices. In order to recoup the investment required to set up the technical, organizational, and personnel infrastructure, audit firms need to consider new pricing approaches (e.g., elements from subscription models or value-based pricing). Despite mixed evidence on new pricing models from both the expert interviews and the survey responses, more senior employees agree significantly stronger with this view. These opinions are valuable as more senior employees should have a better insight into strategic matters. In addition to new pricing models, a stronger focus on the final report is needed. Focusing on this the key deliverable of due diligence by introducing such measures as of supplementary dashboard solutions could stimulate both client awareness and willingness to pay.

Research question 3: Level of adoption

14. **The adoption of analytics is still at an early stage – with an approximate adoption rate of 50%.** Prior studies indicate that the advisory services of audit firms, historically among the late adopters of emerging technologies, have recently begun to invest in data analytics. However, the concrete extent (for the sub service line FDD) only becomes apparent in this study: Analytics tools are currently used in every second FDD project across the entire sample (43.5% in the GSANL region). Diametrically opposed to auditing (as outlined in the literature review in Chapter 4), the Big Four use commercial software that, once being tailored to specific needs, facilitates automation. The Next Ten firms, on the other hand, rely on traditional software (Microsoft Excel) and on proprietary solutions developed in-house.
15. **Usage varies significantly between project settings, individual characteristics, and organizational parameters.** Depending on the project setting, the cost-benefit trade-off outlined previously is used to decide in favor of or against the use of analytics (see statement 9). Moreover, personal and institutional factors explain the differences in use (standard deviation: 28.8%). The adoption rate is significantly higher for women, younger and more junior consultants, employees working for the deals analytics departments, those employed by the Big Four, and those working in the U.S. The institutional differences are evident not only in the question of the adoption rate (*extent*), but also in various questions of use (*approach*). These respective groups can be regarded as frontrunners in FDD.

Research question 4: Adoption factors

16. **At the organizational level, adoption decisions are primarily fueled by firm characteristics (linking structures, size, slack) and the competitive situation.** Competitive pressure, rather than client demand, has triggered audit firms' decisions to adopt analytics in the context of FDD, which has led to a technology push into the market. In addition to seeking to improve process efficiency, audit firms and their top management also strive to create first mover advantages and differentiate themselves from the competition. Among FDD service providers, the Big Four are leading the way due to advantages in size (and associated financial resources), slack, and strong linking structures. These factors facilitate the development of technical know-how (e.g., in analytics champion programs) and the establishment of the necessary personnel and organizational infrastructure (e.g., CoEs, SSCs). Due to the structural disadvantages of non-Big Four companies, it

is not expected that the adoption gap can be closed in the foreseeable future. Among the leading four audit firms, decentrally organized players have created slight first mover advantages; however, large-scale adoption is more difficult as these companies lack alignment between the various users of analytics globally. Thus, the different roles of the adoption-critical factors may alter with time.

17. **At the individual level, social influence has a strong impact – irrespective of voluntariness and experience.** The by far strongest predictor of behavioral intention is social influence (e.g., through analytics champion programs). Typically, this factor has a strong effect in the early stages of adoption, which is the case in the present study. According to the original UTAUT, social influence is significant only in mandatory settings (social pressure) and diminishes over time as the knowledge of prospective adopters increases and allows the formation of individual beliefs. This study, however, finds neither perceived voluntariness nor experience to moderate the relationship of social influence and adoption. This indicates that social influence will continue to have a strong impact on adoption going forward. The strength of the relationship is (i) massively underestimated by the technology-oriented experts interviewed, which has important repercussions for management, and (ii) rarely considered in the mostly qualitative adoption literature in finance and accounting, leading to implications for future research.
18. **Performance expectancy and facilitating conditions support adoption.** Performance expectancy, i.e., the perceived improvements in terms of time (efficiency) and quality (effectiveness), significantly encourages individuals' intentions to adopt analytics tools. Moreover, facilitating conditions, which are considered a hygiene factor in the expert assessments, have the expected direct, positive effect on adoption. Both factors offer possible fields of action to further increase adoption.
19. **Surprisingly, effort expectancy does not significantly contribute to individual adoption.** Easier training and user-friendliness do not promote adoption. In previous UTAUT-related research, the effort expectancy is the least strong (Dwivedi et al., 2011) and most frequently insignificant (Williams et al., 2015) of the four constructs. Especially, "[i]n studies involving professional users […], ease of use is often subordinate to usefulness" (Pynoo et al., 2011, p. 573). Besides its inferior role in a professional environment, experience's significant cross-over interaction effect could be essential to the main effect's insignificance. Nonetheless, this result is surprising in light of the qualitative analysis, in which experts describe effort expectancy as the most important driver of adoption. This misperception has

vital managerial consequences. Finally, results from previous finance and accounting research indicate that effort expectancy is more important for advanced, more complex tools than it is for basic functions (Kim et al., 2009), as the need for advanced skills increases with complexity. In line with the predicted shift towards a stronger insight and value-orientation (see statement 7) and the correspondingly rising use of advanced functionalities, effort expectancy could therefore become a significant adoption factor in the future.

Based on the above statements, practically relevant guidance and implications for finance and accounting research are derived and presented in the subsequent sections.

7.3 Managerial implications

The practical implications presented in the following are divided according to their addressees: FDD service providers, sellers, and investors.

FDD service providers

The empirical results presented in this dissertation can be helpful in five ways for audit firms that offer FDD services. First, the results can serve as a benchmark for practitioners to evaluate their companies' level of adoption and approach to using analytics. This aspect is of particular importance as audit firms currently lack a comprehensive understanding of the market (e.g., due to limited previous research). Second, the broad spectrum of detailed explanations, and examples of concrete applications, enable audit firms to incorporate new use cases and further enhance their analytics offerings. Third, the conceptual framework dealing with the determinants of analytics usage in individual FDD projects can serve as a reference in practice. The guidelines for deciding whether analytics tools can or should be used are either missing or very simple (e.g., revenue-based) and are ripe for more sophisticated designs. This could increase the decision certainty for less experienced FDD advisors. Fourth, numerous potential changes in the conduct of FDD presented in this dissertation will certainly serve as a thought-provoking impetus to change for the leadership teams of audit companies. They encompass a broad spectrum of technological (e.g., possible future applications), processual (e.g., extended scope and increasing link to other due diligence forms and beyond), personnel (e.g., cross-functional staffing), and strategic (e.g., effects on the business model) aspects. Fifth, the findings related to critical adoption factors can be employed as guidelines for practitioners in their efforts to promote the use of data analytics in their organizations. Although accounting firms can difficultly influence most of the determinants at the organizational level, two aspects are of particular relevance:

- **Linking agents can foster large-scale adoption in decentralized networks.** Decentrally organized audit firms have acquired slight first mover advantages in the early stages. The impending hurdle to implementing analytics on a large scale is more difficult for these actors than for centralized organizations. However, globally harmonized implementation is essential to fully exploit efficiency benefits, as it allows the use of the same technical and organizational infrastructure, the same knowledge, the same working methods, and the exchange of experts in the international network. One possible approach to achieving global alignment in decentralized organizations could be to use linking agents that already exist at the national level (e.g., analytics champions, secondees), but not at supranational level.
- **Taking the client's perspective could lead to increased awareness and ultimately demand.** According to the qualitative analysis, clients lack awareness of analytics-based due diligence services. The primary cause is the absence of analytics-induced changes that are tangible to the client, as the changes that relate to data processing are mainly invisible. Audit firms could therefore raise awareness, on the one hand, by reinforcing the benefits resulting from invisible changes (e.g., in proposals and pitches, at their company events) and, on the other hand, by creating visible changes in client discussions and deliverables (e.g. via dashboard solutions).

Based on the findings of this work, audit firms can take a highly targeted approach to foster adoption at the individual level. The following suggested actions can be derived from the findings of this thesis:

- **Greater emphasis on social influence can encourage adoption, particularly through support from senior management.** The interviewed experts, who represent a technology-oriented group, must acknowledge the importance of social influence as an adoption factor. The importance of this adoption factor manifests the need to further strengthen the perception of the social determinant by FDD professionals. Key colleagues are already perceived as role models and current users are attributed a strong profile. Strengthening the role of such users (e.g., analytics champions) as promoters could further increase adoption. The greatest effect in promoting adoption through social influence can, however, be achieved through greater support from senior management.

Despite the high level of awareness and promotion of analytics efforts by the firms' partners, which is attributed by the experts interviewed, this factor lags significantly behind in the quantitative analysis. Leadership endorsement is perceived to be comparatively weak, especially among Next Ten companies, the transaction services department, and in the GSANL region. According to the experts, aligning financial incentives for executives with the use of analytics (e.g., by rewarding investment in training) could stimulate support from senior management. In addition, cultural change management is needed to accustom senior managers and directors to new ways of working.

- **Attaining and highlighting efficiency improvements can enhance performance expectancy and ultimately adoption.** As demonstrated in this thesis, the use of analytics tools leads to improvements in efficiency (time) and effectiveness (quality). Improvements in efficiency are rated as lower but have a greater influence on the intention to adopt. Consequently, audit firms are well advised to focus on further increasing process efficiency, especially in the still largely manual data management activities, and to emphasize the related benefits. According to the qualitative analysis, emphasizing the benefits can be achieved by promoting as specific use cases as possible. Finally, the item that measures career benefits associated with the use of analytics is excluded from the analysis. Nonetheless, its low survey values demonstrate that using analytics tools could be more tightly linked to promotions or remuneration. Although not statistically proven, a positive impact from corresponding measures on the intention to adopt appears plausible.
- **Strengthening knowledge acquisition and training is a cornerstone of fostering adoption.** Of the three facilitating conditions parameters (availability of resources, availability of knowledge, software compatibility), the availability of knowledge is rated lowest but has the highest impact. Consequently, and in line with the qualitative analysis, audit firms should both strengthen their efforts to educate their staff (e.g., incentivizing participation in training) and to facilitate knowledge sharing within their organizations (e.g., knowledge management).
- **Professionals appreciate training sessions that are tailored to their individual level of experience.** Survey respondents consistently report low values for all determinants of effort expectancy. In contrast to the expectations raised in the qualitative analysis, however, neither do low values imply a low inten-

tion to adopt analytics tools nor do high values enhance this intention. A potential cause for the insignificant influence of effort expectancy could be a cross-over interaction effect of experience. This effect indicates that experienced professionals would appreciate more difficult tasks, while the opposite is true for less experienced staff. The effect unveils the need for audit firms to tailor their training more specifically to the level of experience of their staff.

The suggested actions presented above are not exhaustive. For example, further possible elements for increasing IT adoption in the pre-implementation stage (design characteristics, user participation, management support, incentive alignment) and in the post-implementation stage (training, organizational support, peer support) can be found in the study by Venkatesh and Bala (2008).

Sellers

Despite the focus on the supply side (audit firms) rather than demand side (especially sellers and investors) of FDD, important implications arise for the latter. In particular, this thesis raises awareness of the possible use of analytics in FDD, presents the advantages of using analytics over traditional approaches, and outlines situations in which the use is particularly beneficial (e.g., in carve-out transactions). This improved understanding could be helpful for vendors when awarding the commission for FDD projects, e.g. by formulating concrete expectations of the providers' analytics competences. Moreover, selling parties could consider making their own contributions to improving the FDD process. For instance, the in-house data analytics departments present in large companies could be included in this process to facilitate data provision and extraction. Finally, large groups and holding companies could start reusing parts of the data model (e.g., the mapping logic) for controlling purposes after the divesture.

Investors

This thesis also raises awareness among bidders. This research aims to facilitate and enhance their understanding of the benefits associated with using analytics. In particular, bidders can gain deeper insight into the target company's financial figures, thus narrowing the information gap and uncovering value potential. Value creation is of the utmost importance in times of fierce competition for high-priced assets (e.g., due to high cash reserves/dry powder and a persistently low interest rate environment) and in light of the high failure rates of M&A. Financial investors, who tend to possess less knowledge of the market, customer, and competitive environment of the target company than strategic investors, particularly benefit from the increasingly commercial orientation of FDD. Moreover, the use of analytics can accelerate the due diligence process and thus provide a time advantage over competing bidders. Even in transactions with an exclusive negotiation situation, i.e., without competitive bidders, the higher transparency allows for a more fact-based argumentation and could consequently reduce the need for discussion with the sell-side. These obvious advantages associated with the use of analytics, together with the assessment of the interviewees, underscore that a lack of awareness is the primary reason for the lack of demand for the application of analytics. This thesis can hopefully help counteract this situation. If, however, investors empower audit firms to employ analytics, the investors must find approaches to cope with the corresponding constraints (e.g., extension of the lead time, inability to share interim results).

7.4 Research implications

In the following, implications for the four areas of research covered in this thesis are presented: finance and accounting, M&A and due diligence, big data and data analytics, and technology adoption.

Finance and accounting research

As outlined in the introductory chapter, Gepp et al. (2018) state that research in finance and accounting related to big data and data analytics is limited to only four research streams. Although there are now a few studies outside these four areas (e.g., in the field of managerial accounting), it can be generally confirmed that research on these big data and data analytics is scant in finance and accounting. However, the use cases that are widespread in practice go beyond the four research streams and are also relevant to other areas. Therefore, this dissertation strives to expand existing literature with a new research vein: FDD.

Only two articles, both published while this thesis was in progress, deal with data analytics in FDD. Therefore, adjacent literature, especially from auditing research, is used. This approach has two implications for finance and accounting research on big data and data analytics. First, it underscores that the different research directions are sufficiently interrelated to be able to transfer general ideas from adjacent literature to emerging research veins. However, the specificities of each area already require separate research in genealogies beyond the existing four. Second, the review of existing studies and their research approaches reveals that a greater alignment to practice is required.

Moreover, concrete implications for the three topics of big data, data analytics, and technology adoption arise from this thesis. Numerous research papers suggest how big data can be integrated into accounting work. However, these suggestions (such as the use of unstructured data types, especially audio, image, and video data) have often turned out not be relevant – at least for FDD practice. A critical reflection on the actual practical applicability of these academic suggestions is needed. Moreover, large parts of previous literature that deal with analytics neither sufficiently link the analytics techniques used to the underlying data nor do they regard analytics in conjunction with previous data management activities. Finance and accounting research could therefore benefit from taking a different, more holistic lens to the topic of analytics. Finally, adoption research, which is crucial to understanding a technology's practical application, is currently mainly qualitative in nature and not grounded in established adoption theories. Thus, a more systematic review is needed.

M&A and due diligence research

This thesis adopts the process view (as opposed to the content view) when considering digitalization in M&A. Accordingly, research on the M&A process in general, and the FDD process in particular, benefits from the results of both literature study and empirical analysis.

Prior publications demonstrate obvious limitations in their examinations of FDD's objectives. These previous articles were incomplete (i.e., listed only a few objects), unsystematic, or not focused enough in FDD. This thesis seeks to rectify these limitations by employing an FDD-specific scheme. Moreover, a process framework supports the in-depth review of all process phases. This holistic view is likely to gain in importance as the increasing use of analytics software leads to an extension of the preparation phase and the growing popularity of new formats for presenting results in the reporting phase. Concentrating purely on the analyses of FDD and the report in a classic format will therefore be insufficient in the future. The expansion of the areas of analysis, especially in the direction of commercial aspects, must also be taken into account. Simultaneously, there is a growing need to more closely consider the interfaces of FDD, both with other due diligence forms and with other work streams in the M&A process.

With regard to the application of big data and analytics software, this thesis offers unprecedented insights and seeks to establish another research stream in the finance and accounting domain. This thesis is compelling in its breadth and depth, it erects a strong foundation for numerous new research projects to build upon. For example, the research of this thesis could be expanded upon (e.g., focus on initiators instead of service providers, additional countries, further activities in the M&A process, or other technologies) or future studies could examine selected topics of this thesis in more detail (e.g., possible changes in the business models of service providers, quantification of implications of analytics usage on the deal process and success). Future research will also necessitate a recourse to adjacent literature as only two other studies, besides this thesis, have examined analytics in FDD. Therefore, research methods that involve practitioners (e.g., interviews, questionnaires, case studies) are particularly suitable for future investigations.

Big data and analytics research

This paper explains important terminologies and concepts related to big data and data analytics. Future research should consider the distinctions outlined. Too often, vogue expressions (e.g., big data, advanced analytics) are still used without the necessary conceptual understanding, an obstacle both in practice and in research. After reviewing a broad spectrum of adjacent literature, it can be discerned that this observation particularly applies to research that attempts to transfer the use of novel technologies to new areas of application (e.g., finance and accounting).

In addition, studies examining the use of analytics should also take into account both the data analyzed (as already proposed by Alles and Gray, 2016; Ruhnke, 2019) and the necessary data management activities. In current studies these connections are often missing, leading to an incomplete picture. In contrast, this thesis demonstrates that an understanding of the use not only of analytics but also of data management is crucial – especially in the early stages of adoption.

Technology adoption research

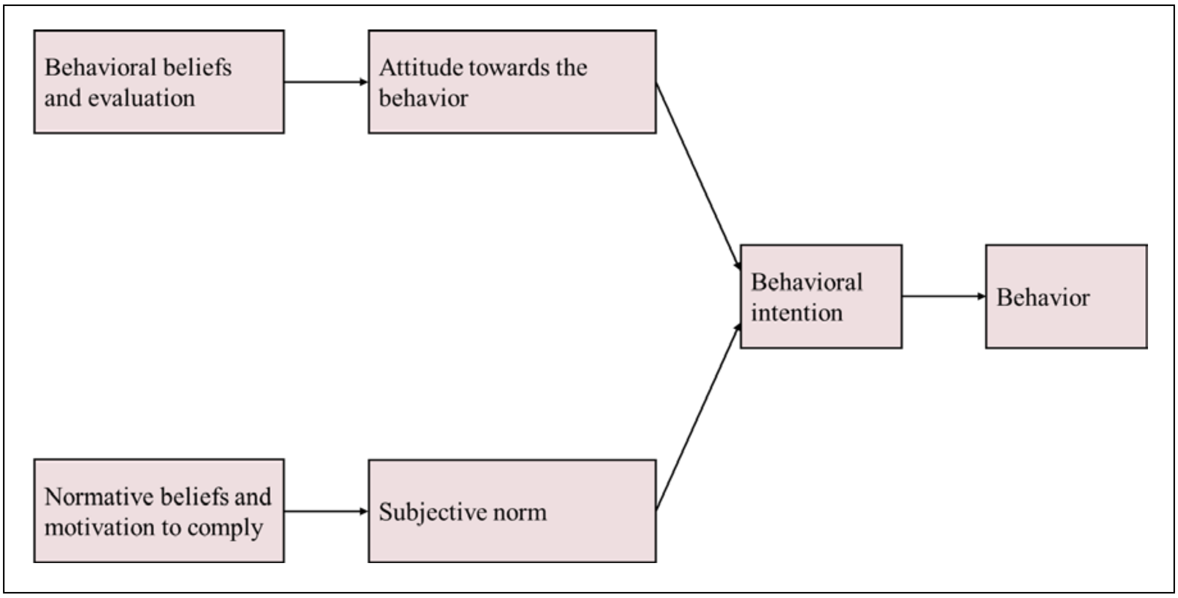
This thesis resolves the shortcoming that the vast majority of existing adoption research does not consider adoption holistically, i.e., both at the organizational (TOE framework) and at the individual (UTAUT) level. As a first step, the large spectrum of 16 adoption models and extensions, as well as the current state of adoption literature in finance and accounting, are reviewed. This makes it possible to refine the theoretical models by identifying previously unrecognized adoption factors requiring empirical validation. For instance, going forward, (although it is not a critical adoption factor in the context of this study) researchers should include the client perspective in the TOE framework when examining the adoption of service providers that integrate IT into their product offerings or service delivery. Subsequent to the literature review, a qualitative and a quantitative analysis reveal critical adoption factors. The qualitative analysis helps to further extend or modify the theoretical models. For example, hierarchy level was identified as a potential moderator and further theoretically established interactions were modified to the specific context at hand. Unlike most previous adoption studies analyzing the UTAUT, which concentrate on the main effects, this thesis also considers interaction effects. This in-depth analysis uniquely reveals a cross-over interaction effect of experience, which helps to (partially) explain the insignificant main effect of effort expectancies. The need for context-specific research is underscored by the study results, especially the high weight of social influence and the insignificance of effort expectancy. Finally, concrete guidance for the leadership of FDD service providers to increase adoption is derived from the critical adoption factors identified in this research.

Overall, the thesis contributes to adoption research by demonstrating the importance of (i) taking a comprehensive, i.e., organizational and individual, perspective on adoption, (ii) selecting the theoretical frameworks according to the concrete research context, (iii) tailoring the research models based on both a literature review and expert interviews, and (iv) investigating the models in their entirety (e.g., including interaction effects).

Appendix

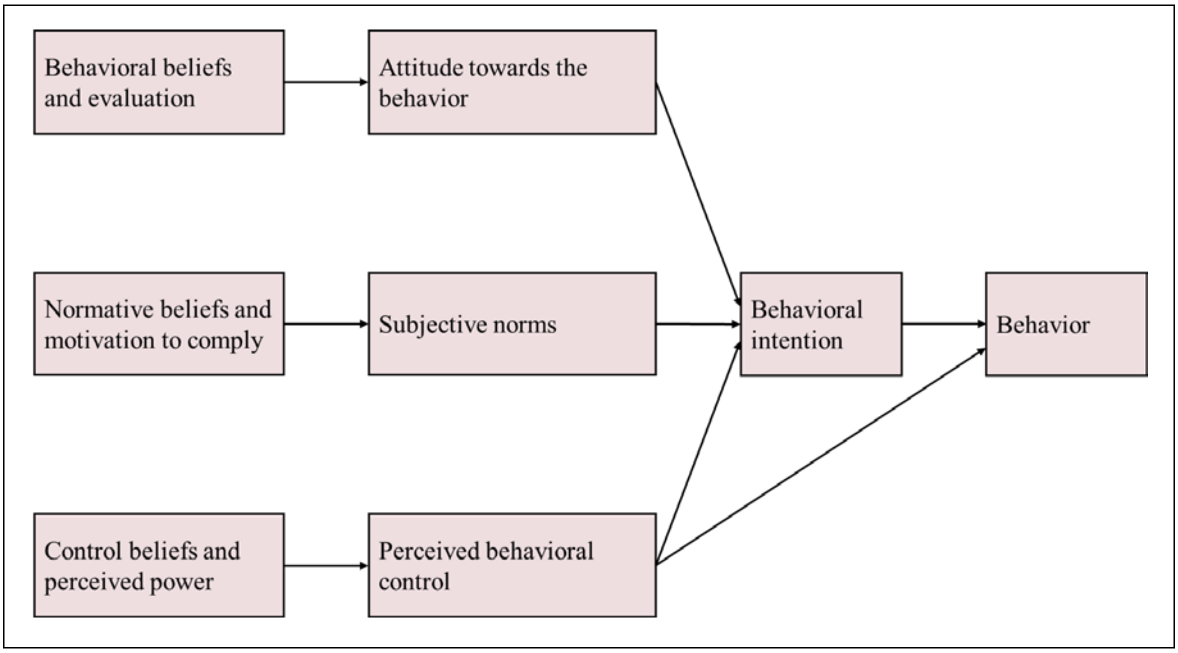
Appendix 1: Technology adoption theories

Figure A.1: Theory of Reasoned Action



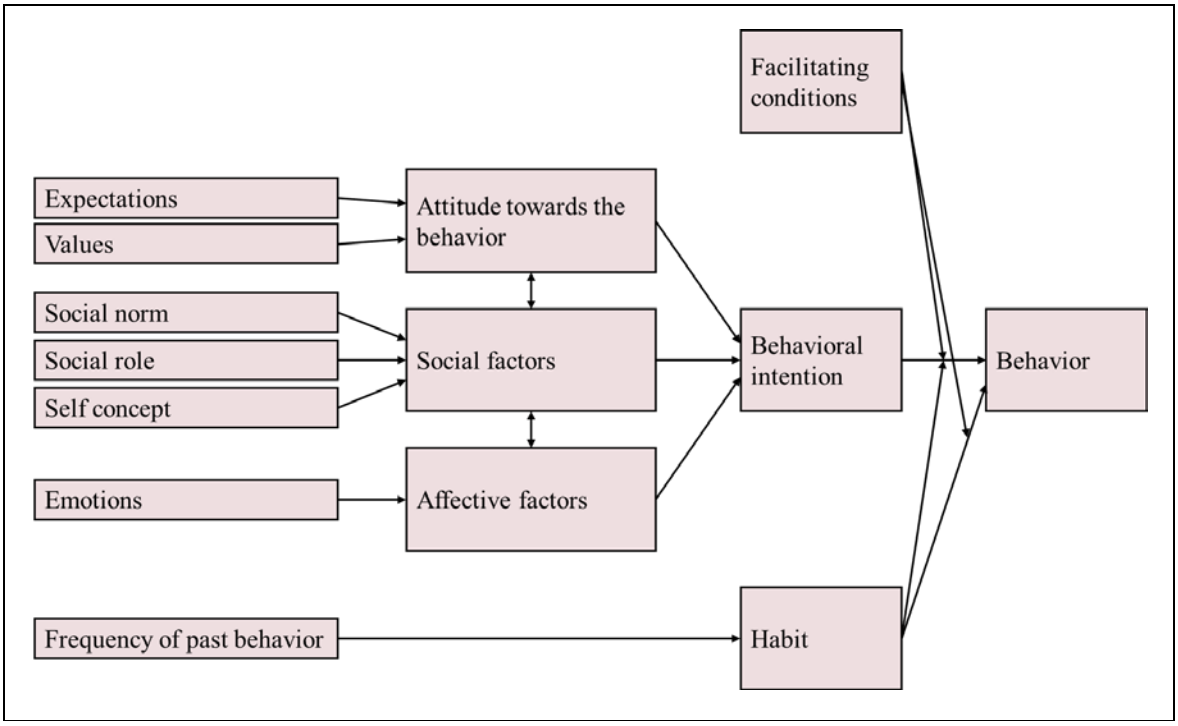
Source: Own illustration based on Ajzen and Fishbein (1980) and Fishbein and Ajzen (1975)

Figure A.2: Theory of Planned Behavior



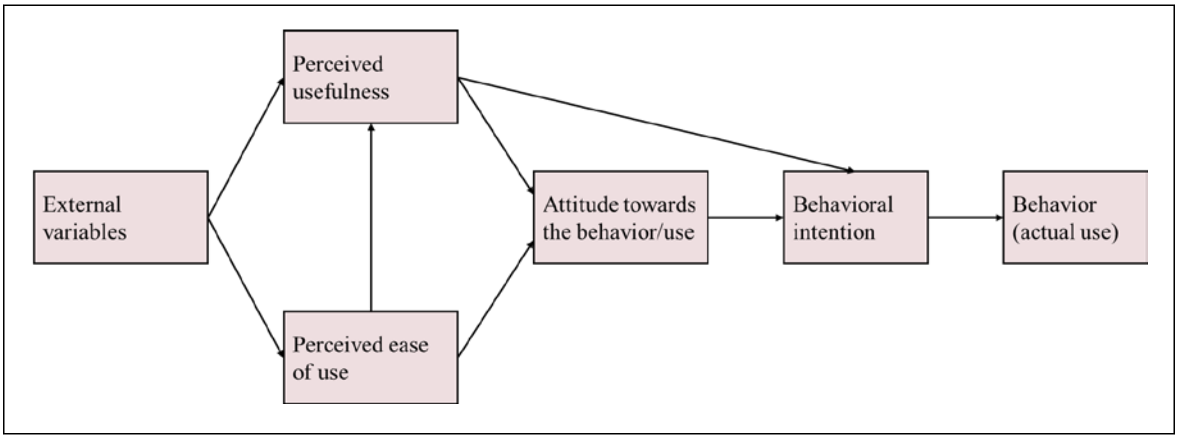
Source: Own illustration based on Ajzen (1985, 1991)

Figure A.3: Theory of Interpersonal Behavior



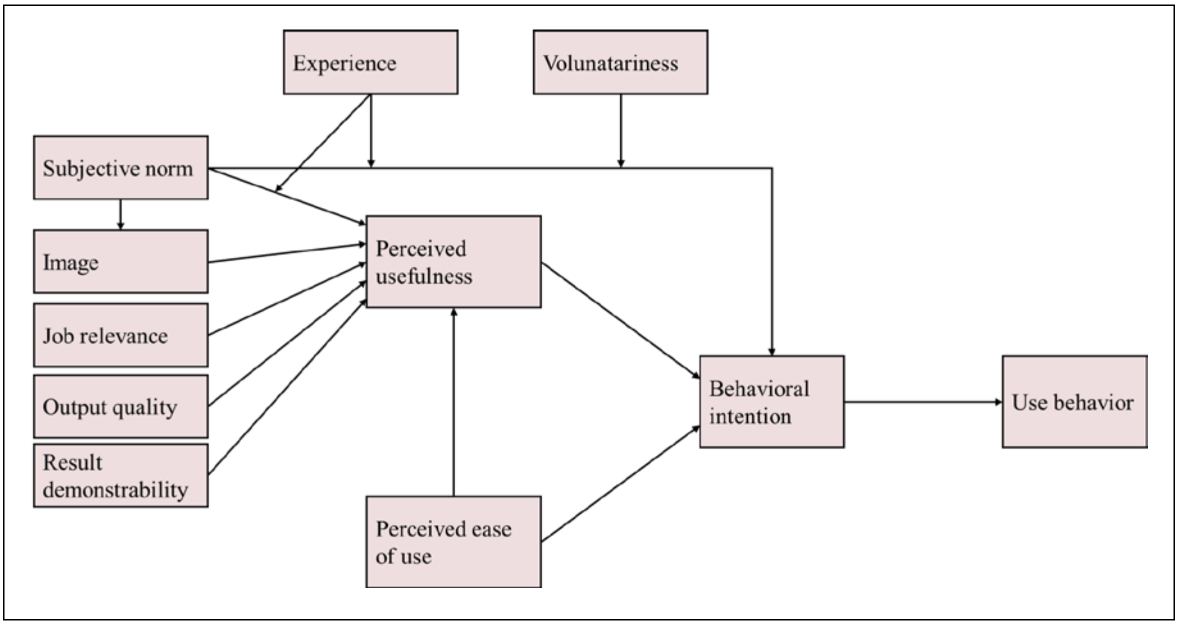
Source: Own illustration based on Triandis (1977, 1980)

Figure A.4: Technology Acceptance Model



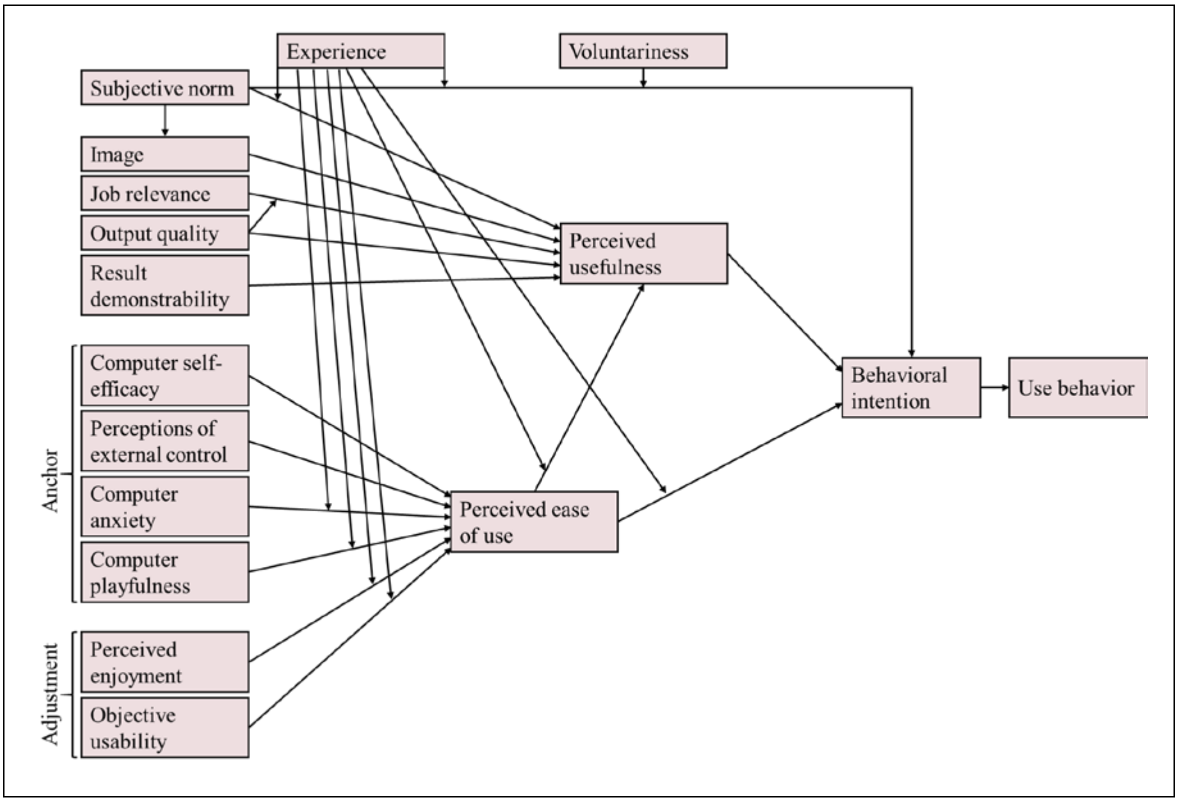
Source: Own illustration based on Davis (1986, 1989) and Davis et al. (1989)

Figure A.5: Technology Acceptance Model 2



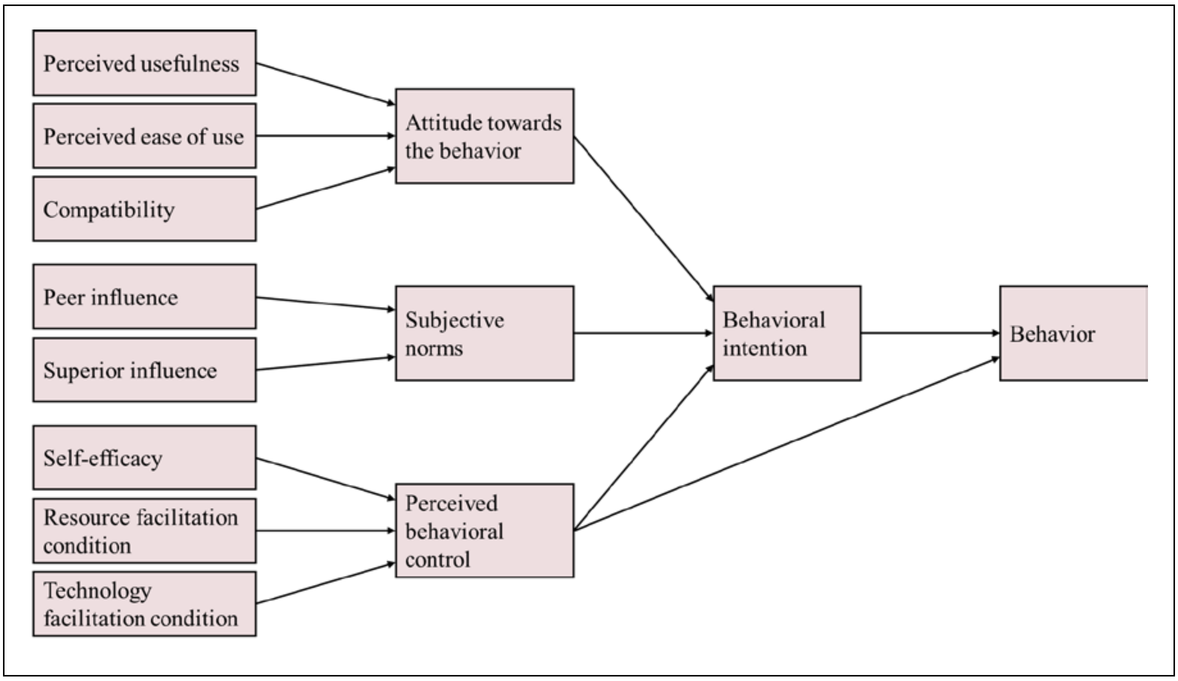
Source: Own illustration based on Venkatesh and Davis (2000)

Figure A.6: Technology Acceptance Model 3



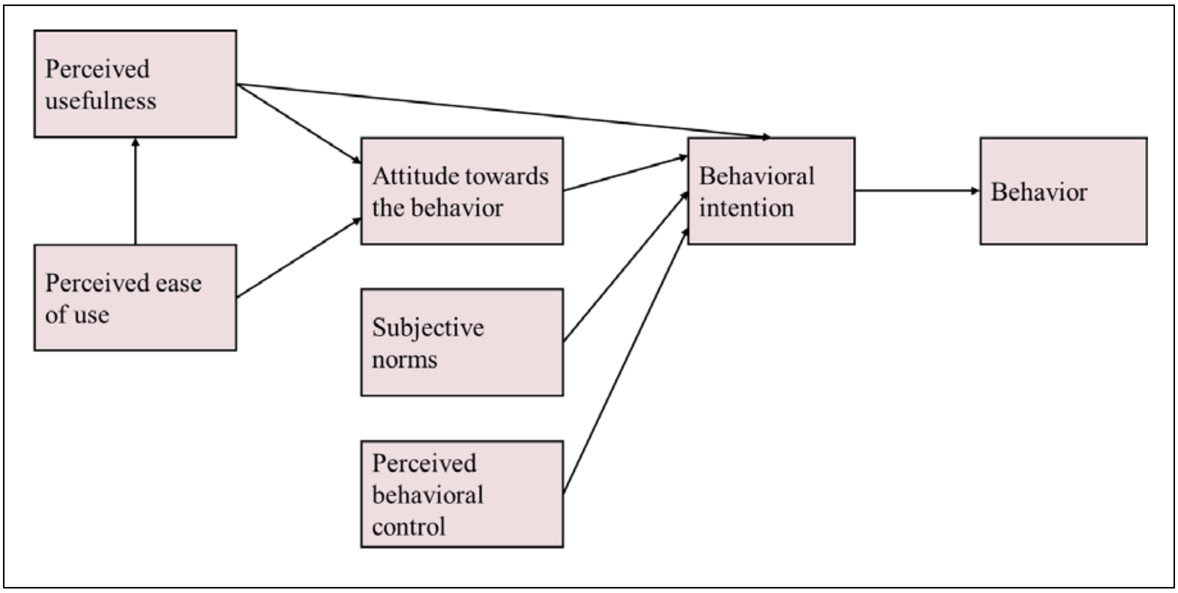
Source: Own illustration based on Venkatesh and Bala (2008)

Figure A.7: Decomposed Theory of Planned Behavior



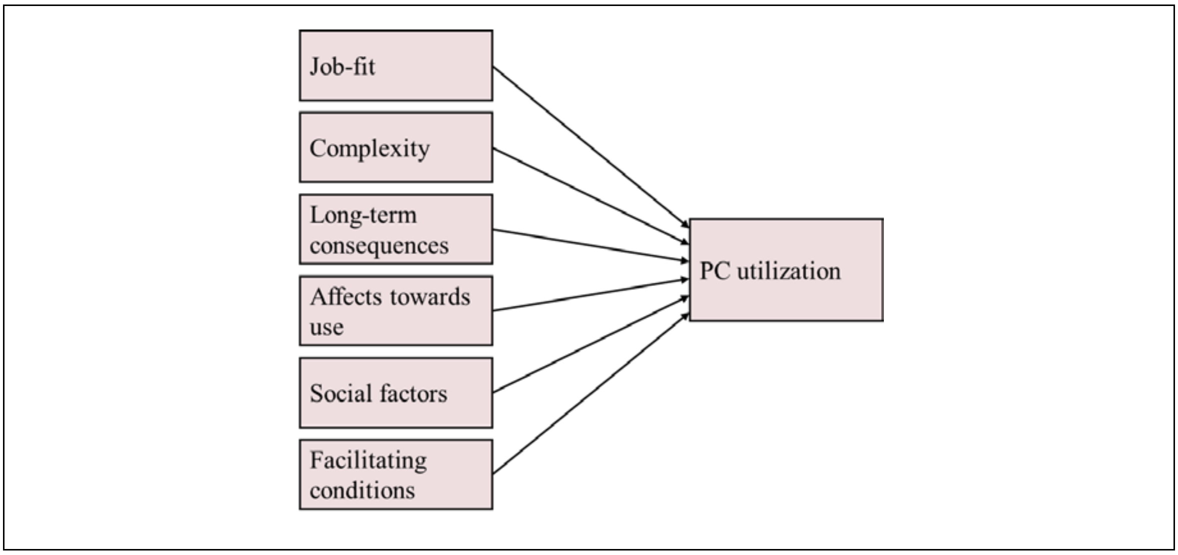
Source: Own illustration based on Taylor and Todd (1995b)

Figure A.8: Combined Technology Acceptance Model and Theory of Planned Behavior



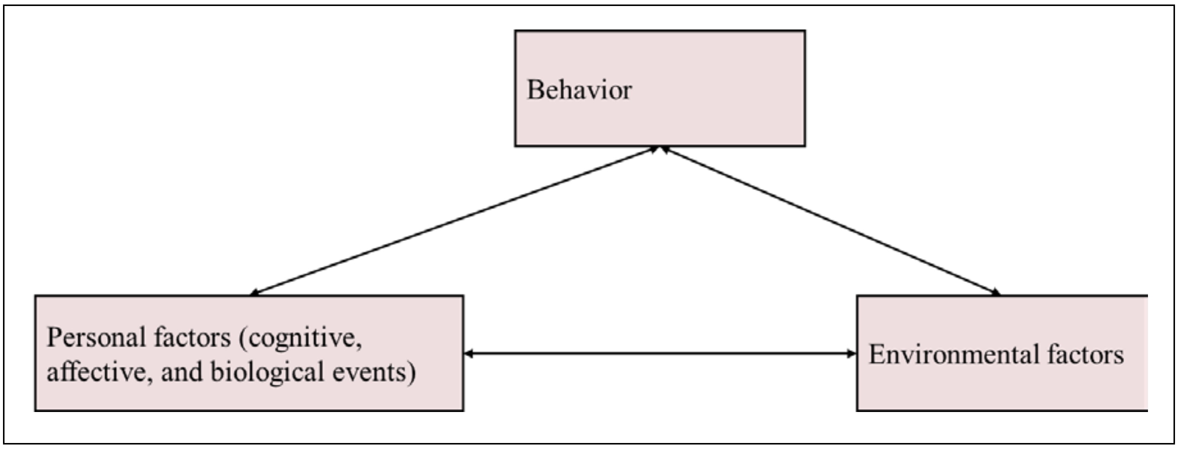
Source: Own illustration based on Taylor and Todd (1995a)

Figure A.9: Model of Personal Computer Utilization



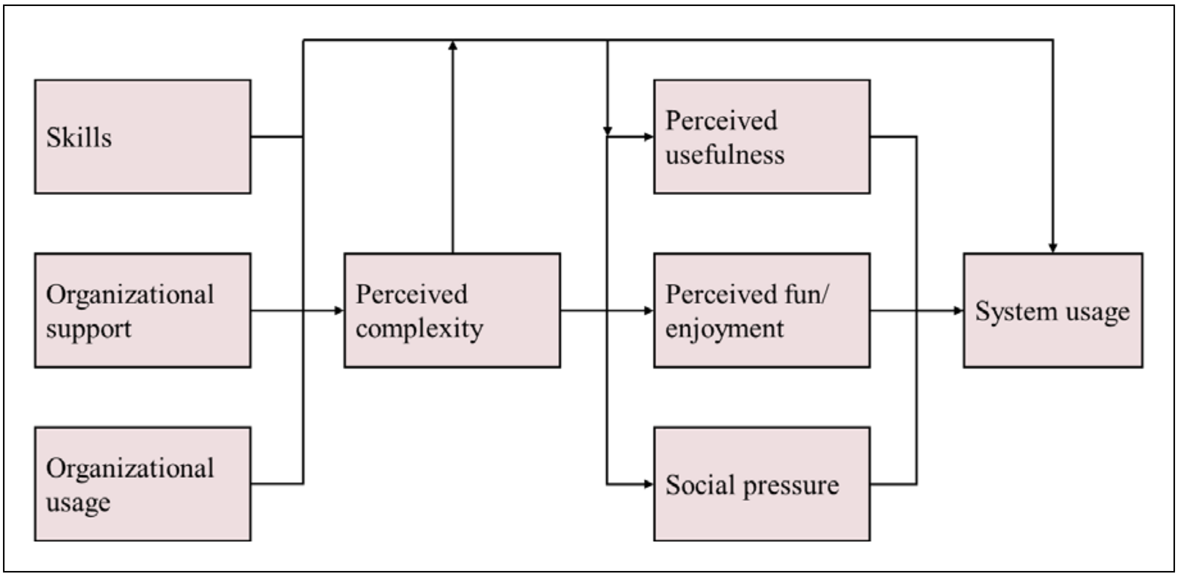
Source: Own illustration based on Thompson et al. (1991)

Figure A.10: Social Cognitive Theory



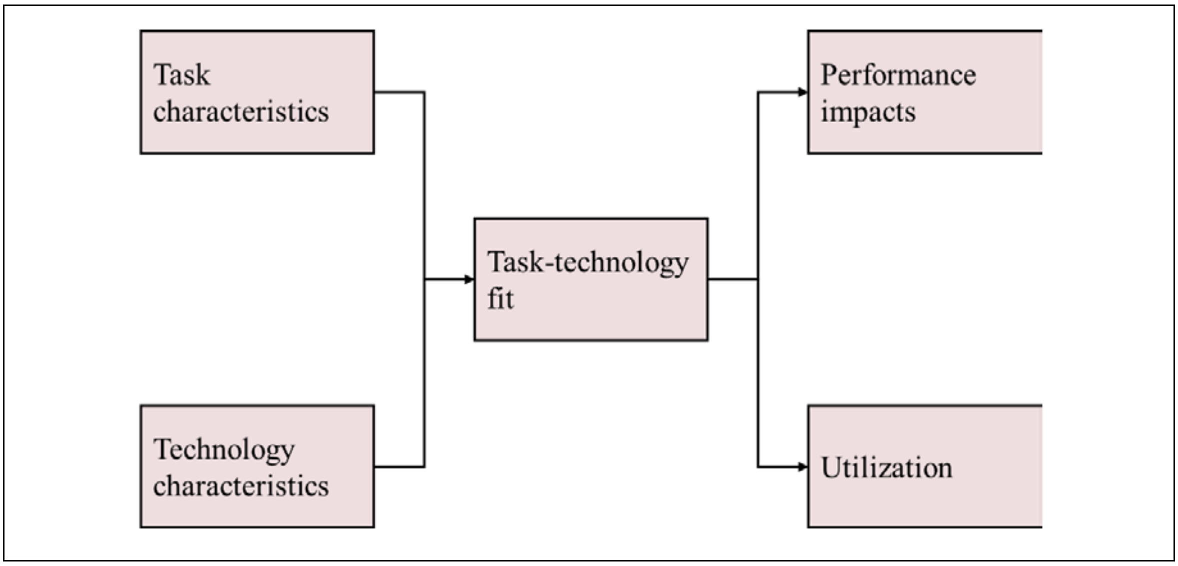
Source: Own illustration based on Bandura (1977, 1978, 1982, 1986)

Figure A.11: Motivational Model



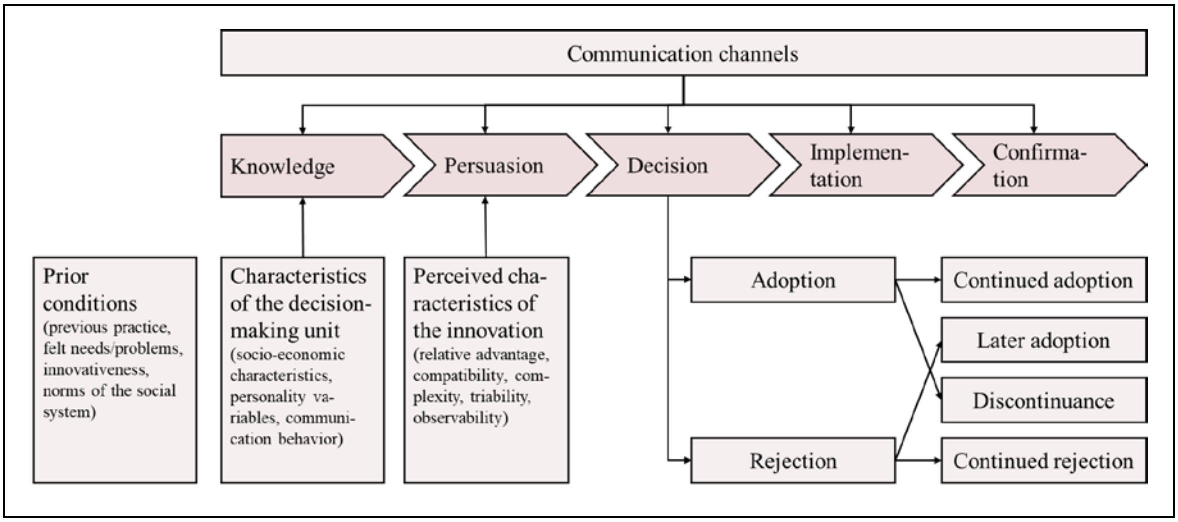
Source: Own illustration based on Igbaria et al. (1996)

Figure A.12: Task-Technology Fit Theory



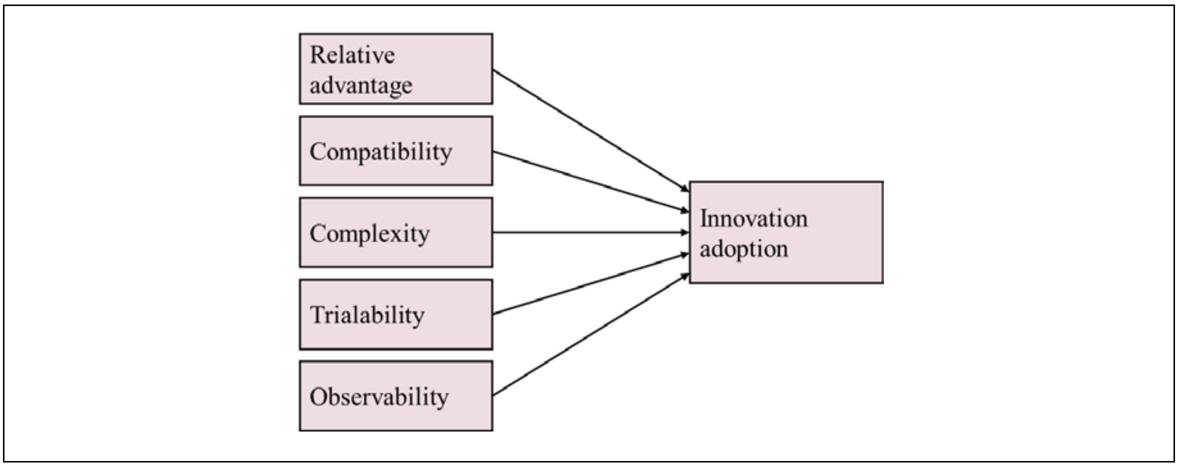
Source: Own illustration based on Goodhue and Thompson (1995)

Figure A.13: Innovation decision process



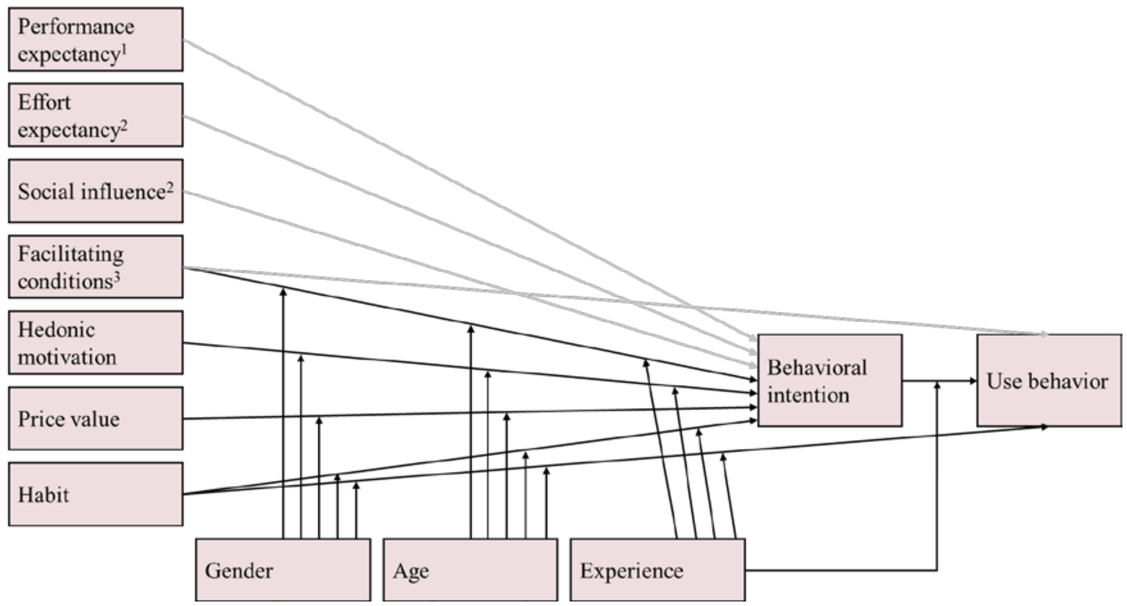
Source: Own illustration based on Rogers (2003)

Figure A.14: Innovation Diffusion Theory



Source: Own illustration based on Rogers (2003)

Figure A.15: Unified Theory of Acceptance and Use of Technology 2



Notes:
Relationships from the original UTAUT are shown as grey lines or indicated as per the footnote. 1) Moderated by age and gender; 2) moderated by age, gender, and experience; 3) effect on use behavior is moderated by age and experience.

Source: Own illustration based on Venkatesh et al. (2012)

Appendix 2: List of expert interviewees

Table A.1: List of expert interviewees

#	Rank	Function	Big Four	Location	P/T	Date[1]	Language	Duration[2]
P1	Partner	Transaction Services	Yes	Frankfurt	T	04/29/2019	German	60
P2	Partner	Transaction Services	Yes	Munich	P	05/13/2019	German	55
P3	Partner	Transaction Services	Yes	Zurich	T	05/22/2019	German	60
P4	Partner	Transaction Services	Yes	Munich	T	11/05/2019	German	40
D1	Director	Deals Analytics	Yes	Frankfurt	P	03/15/2019	German	60
D2	Director	Data and Analytics	Yes	Berlin	T	04/30/2019	German	40
D3	Director	Deals Analytics	Yes	Amsterdam	P	05/08/2019	English	105
D4	Director	Transaction Services	Yes	Copenhagen	T	05/21/2019	English	65
SM1	Sr. Manager	Transaction Services	Yes	Frankfurt	T	05/07/2019	German	30
M1	Manager	Transaction Services	Yes	Frankfurt	P	04/09/2019	German	55
M2	Manager	Transaction Services	Yes	Frankfurt	P	04/09/2019	German	75
M3	Manager	Transaction Services	Yes	Hamburg	T	05/03/2019	German	80
M4	Manager	Deals Analytics	Yes	Zurich	P	06/04/2019	German	85
M5	Manager	Transaction Services	No	Hamburg	T	07/08/2019	German	50
M6	Manager	Transaction Services	Yes	Zurich	T	10/10/2019	German	70
SC1	Sr. Consultant	Transaction Services	Yes	Frankfurt	T	04/17/2019	German	75
SC2	Sr. Consultant	Transaction Services	Yes	Frankfurt	T	04/18/2019	German	60
SC3	Sr. Consultant	Deals Analytics	Yes	Munich	P	04/29/2019	German	80
SC4	Sr. Consultant	Transaction Services	Yes	Düsseldorf	T	05/03/2019	English	60
SC5	Sr. Consultant	Transaction Services	Yes	Frankfurt	T	05/18/2019	German	65

Variables definition:
P = in person (face-to-face)
T= by telephone

Notes:
1) The date is indicated in mm/dd/yyyy format.
2) The duration is indicated in minutes.
The 20 interviewees are classified according to their hierarchy levels and are subsequently numbered in chronological order (from earlier to later interviews). The hierarchy levels and service lines are adjusted across companies to ensure the anonymity of the interviewees.

Source: Own illustration

Appendix 3: Catalogue of questions for semi-structured expert interviews

As part of the formal interview request, the interview partners received a comprehensive brochure that contained information about (i) the study and the researcher, (ii) the interviewee selection approach, (iii) the mode of the interviews and the interview process as well as (iv) aspects of confidentiality and data privacy.

Before the interview, the catalogue of questions was handed over to the interview partners in both German and English. It consisted of 48 questions in six categories (corresponding to the four research questions as well as one introduction category and concluding category), as shown in Table A.2.

In each of the interviews a selection of the questions was ultimately posed.

Table A.2: Catalogue of questions for semi-structured expert interviews

Questions per category
Introduction
• Could you please briefly describe your professional role and how it relates to data analytics?
Use of data and information
• Which data is processed nowadays in FDD and how has the type of data analyzed changed over time? • What factors cause the changes previously described? • How has the analysis of financial information changed over time? • Which additional non-financial information is analyzed? • In which process steps and analyses of FDD is non-financial information included and for which reason? • Which types of big data (e.g., from the following categories: text documents, web and social media data, transactional data, sensor data, geolocational/geospatial data, audio data, image data, video data) are used in FDD? • In which process steps and analyses of FDD is big data included and for which reason? • Which data sources are used? • How has the access to information evolved since the establishment of virtual data rooms? • What are critical determinants of data availability in FDD? • In how many sell-side and buy-side FDD projects, respectively, (in %) is big data already analyzed? • What consequences does the inclusion of non-financial data (or even big data) have for the FDD process?
Use of data analytics
• Which opportunities does the use of data analytics in FDD offer to service providers? • Which opportunities does the use of data analytics in FDD offer to sellers, investors, and lenders? • How is data analytics used in the preparation phase of the FDD process? • How is data analytics used in the different areas of the analysis phase of the FDD process (profitability analysis, balance sheet analysis, cash flow analysis, business plan validation)? • How is data analytics used in the reporting phase of the FDD process? • In which process steps is data analytics applied most often and least often, respectively? • Which data analytics orientations (descriptive, predictive, prescriptive) and corresponding techniques are used? • Which data analytics tools are employed? • What industry specifics have to be considered? • Which specific requirements for strategic and financial investors, respectively, have to be considered? • Where does the use of data analytics have similarities to other parts of your business (e.g., auditing)? • What consequences does the use of data analytics have for the FDD process? • What consequences does the use of data analytics have for service providers (e.g., concerning recruitment, infrastructure, business model)?

Level of adoption
• What has been the starting point to introduce data analytics in the FDD process? • In how many FDD projects (in %) is data analytics already applied? • By which factors should the adoption level be distinguished?
Adoption factors
• Which challenges need to be overcome to use data analytics to a larger extent? • How does data analytics software itself (e.g., availability, characteristics) affect adoption? • Which role do economic considerations (e.g., cost-benefit ratio) play in adoption decisions? • How do organizational aspects (e.g., linking structures, organizational structure, top management support, firm size, slack resources) affect adoption? • How does competition affect adoption? • What role does client demand play in adoption? • To what extent do regulatory aspects (e.g., data security laws) or liability concerns affect adoption? • Are there any other factors that influence an organization's adoption decisions? • To what extent does the performance expectancy associated with data analytics support adoption? • What factors affect this performance expectancy? • To what extent does the effort expectancy associated with data analytics support adoption? • What factors affect this effort expectancy? • To what extent does the social influence associated with the use of data analytics support adoption? • What factors affect this social influence? • To what extent does the technical and personnel infrastructure support adoption? • Are there any other factors that influence individual's adoption decisions? • What needs to change in order to increase adoption?
Conclusion
• Is there anything you would like to add that we have not discussed yet? • Do you have any questions for me?

Source: Own illustration

Appendix 4: Invitation letter and questionnaire

The figures below depict the English version of the invitation letter and the questionnaire. The German versions will be provided on request.

Figure A.16: Invitation letter

University of St.Gallen

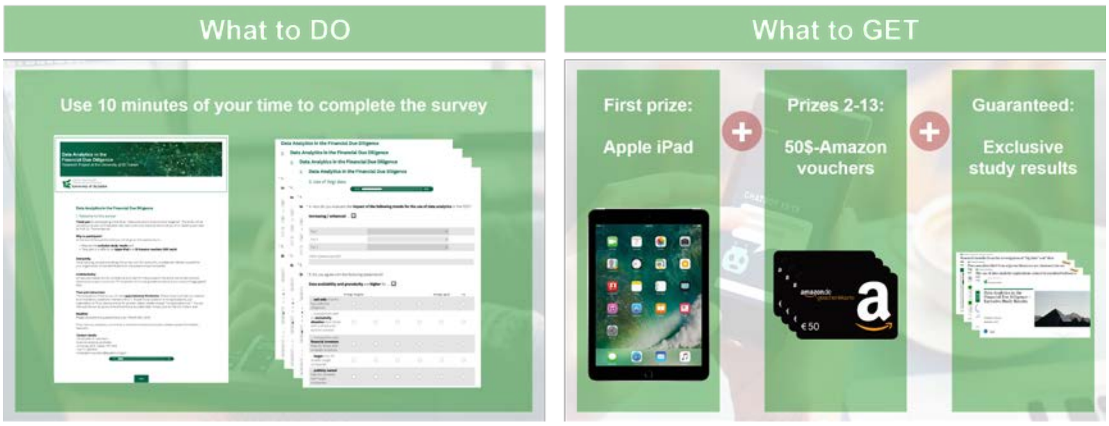
Institut für Finanzwissenschaft,
Finanzrecht und Law and Economics

Dear Sir or Madam,

I would be delighted if you would take part in the following **survey** on **"Data Analytics in Financial Due Diligence"** as part of my doctoral thesis at the University of St. Gallen.

Each participant will be invited to …

- … receive the exclusively prepared study results and
- … take part in the raffle for an Apple iPad and 12 Amazon vouchers (€/$50 each).



To participate simply click on the following link and fill out the **10-minute** survey. Your data will of course be treated **anonymously and confidentially**. The survey is addressed to all due diligence consultants from the Big Four and Next Ten auditing firms and may therefore be forwarded to the appropriate people.

or >> **Survey link** **(EN)** <<, respectively.

Thank you in advance for your help with my dissertation. I am looking forward to your comments and suggestions.

Best regards,
Christopher M. Neumann

Figure A.17: Questionnaire

Data Analytics in the Financial Due Diligence (FDD)

1. Welcome to this survey!

Thank you for participating in the study "Data Analytics in the Financial Due Diligence".

The study will be carried out as part of my doctoral thesis at the University of St. Gallen supervised by Prof. Dr. Thomas Berndt. It contains 22 questions in **five thematic blocks**:

- Introduction
- Use of (big) data
- Use of data analytics tools
- Adoption/acceptance (theory-based)
- Implications and trends

Why to participate?
At the end of the questionnaire you will be given the opportunity to ...

- ... request the **study results exclusively prepared for participants** and
- ... take part in a raffle for an **Apple iPad** and **12 Amazon vouchers (50€ each)**.

Time and instructions
The completion of this survey will take **approximately 10 minutes**. Please make sure that you respond to all mandatory questions (marked with a *). If a particular question is not applicable to your organization or if you cannot answer for another reason, please choose “not applicable (n/a)”.

Deadline
Please complete this questionnaire by **October 25, 2019**.

Anonymity
While carrying out and evaluating this survey, your full anonymity is preserved. Neither yourself nor your organization will be identifiable from the questionnaire completed.

Confidentiality
All data are treated strictly confidential and used for the purpose of the above mentioned doctoral dissertation project exclusively. Third parties will only be granted access to anonymized and aggregated data.

If you have any questions, comments, or discussions about the project, please contact me.

Contact details
Christopher M. Neumann
Doctoral candidate
University of St. Gallen, IFF-HSG
+49 171 3397910
christopher.neumann@student.unisg.ch

1 / 8 13%

Next

Data Analytics in the Financial Due Diligence (FDD)

2. Introduction

2 / 8 25%

* 1. How do you evaluate the **impact of data analytics** software on the **FDD process**?

strong negative ○ ○ ○ ○ ○ strong positive ○ n/a

* 2. In your opinion, **how suitable** is data analytics software for the **FDD compared to other M&A-related services**?

much less suitable ○ ○ ○ ○ ○ much more suitable ○ n/a

Previous Next

Data Analytics in the Financial Due Diligence (FDD)

3. Use of (big) data

3 / 8 38%

* 3. Which of the **following trends most stimulate the use of data analytics** in the FDD?
(Please choose up to three options.)

Increasing/enhanced ...

- ☐ ... data availability
- ☐ ... data granularity
- ☐ ... standardization of data formats
- ☐ ... access to the target's source systems (e.g., ERP)
- ☐ ... possibilities of data sharing
- ☐ ... possibilities of data preparation/transformation
- ☐ ... possibilities of data analysis
- ☐ ... clients' requirements/expectations
- ☐ Other (please specify)

* 4. Do you agree with the following statements?

Data availability and granularity are **higher** for ...

	strongly disagree				strongly agree	n/a
... **sell-side** than for buy-side due diligences.	○	○	○	○	○	○
... transactions with an **exclusivity situation** than those with a structured auction process.	○	○	○	○	○	○
... transactions with **financial investors** than for those with strategic investors as sellers (sell-side).	○	○	○	○	○	○
... **larger** than for smaller target companies.	○	○	○	○	○	○
... **publicly owned** than for privately held target companies.	○	○	○	○	○	○
... target companies **held by a financial sponsor** than for those held by private persons.	○	○	○	○	○	○
... target companies with **fragmented** than for those with concentrated customer and product structures.	○	○	○	○	○	○
... target companies with a **data-driven culture** than for those with a data-sensitive culture.	○	○	○	○	○	○

Other (please specify)

* 5. How **often** is the following information **used in the FDD**?

	never				always	n/a
Financial data from the **target** company	○	○	○	○	○	○
Non-financial data from the **target** company	○	○	○	○	○	○
Financial data from **external** sources	○	○	○	○	○	○
Non-financial data from **external** sources	○	○	○	○	○	○

* 6. Which of the following **non-financial data of the target company** do you most frequently incorporate into the FDD?
(Please choose up to three options.)

- ☐ Country data
- ☐ Customer data
- ☐ Operations data
- ☐ Product data
- ☐ Store data
- ☐ Staff/employee data
- ☐ Supplier data
- ☐ No use of non-financial data
- ☐ Other (please specify)

* 7. Which of the following **non-financial data from external sources** do you most frequently incorporate into the FDD?
(Please choose up to three options.)

- ☐ Demographic data
- ☐ Geolocational/-spatial data
- ☐ Sensor/weather data
- ☐ Social media data
- ☐ Transactional/market data
- ☐ Website data
- ☐ No use of non-financial data
- ☐ Other (please specify)

Previous Next

Data Analytics in the Financial Due Diligence (FDD)

4. Use of data analytics tools

4 / 8 50%

* 8. Which are the **"top 3" most used software tools** to prepare and conduct the analyses in an FDD?
(Please choose up to three options.)

Top 1	
Top 2	
Top 3	

Other (please specify)

* 9. Prior to the analysis with data analytics software, do you **typically build a comprehensive data model** ("single version of the truth")?

- yes
- no

* 10. Do you agree with the following statement?

The use of data analytics requires **more time for data preparation** (e.g., cleansing, transforming, mapping) and **less time for data analysis** (e.g., more standardization and automation, quick updates).

strongly disagree				strongly agree	n/a
○	○	○	○	○	○

* 11. Do you agree with the following statement?

Before using data analytics tools, FDD consultants must therefore **consider whether the time savings in the analyses offset the longer lead time for data preparation**.

strongly disagree				strongly agree	n/a
○	○	○	○	○	○

* 12. Which of the following **factors** do you take in account in the **decision whether or not to use** data analytics software?
(You can select any number of options.)

- ☐ Deal **complexity** (esp. divestures vs. sales of an entire group/company)
- ☐ Deal **scope**
- ☐ **Compatibility** with client's IT capabilities
- ☐ **Temporal restrictions**
- ☐ Client's demand for **interim results**
- ☐ **Budget restrictions**
- ☐ Availability of **skilled resources**
- ☐ **Data availability**
- ☐ **Data variety**
- ☐ **Data veracity**
- ☐ Other (please specify)

* 13. How **often** do you apply data analytics in the following **review areas**?

	never				always	n/a
Profitability analysis (incl. quality of earnings)	○	○	○	○	○	○
Balance sheet analysis	○	○	○	○	○	○
Cash flow analysis	○	○	○	○	○	○
Business plan validation	○	○	○	○	○	○

* 14. Which of the following profitability analyses **benefits the most** from investigating **more granular target data using data analytics tools**?
(Please choose up to three options.)

- ☐ Cohort analysis
- ☐ Customer churn analysis
- ☐ Customer lifetime value (CLTV) analysis
- ☐ Identification of one-off or non-operating income/expenses
- ☐ Price-volume analysis
- ☐ Raw material pass through analysis
- ☐ Reconciliations
- ☐ Sum of the parts P&L
- ☐ Transaction effect analysis
- ☐ Translation effect / constant currency analysis
- ☐ Other (please specify)

Previous Next

Data Analytics in the Financial Due Diligence (FDD)

5. Adoption/acceptance (theory-based)

5 / 8 63%

* 15. In **how many** FDD projects do you use **data analytics tools instead of traditional solutions**?

0% 100%

* 16. How do you assess your **current level of experience** with different data analytics features?

	novice						expert	n/a
Data management (esp. data transformation)	○	○	○	○	○	○	○	○
Descriptive analytics	○	○	○	○	○	○	○	○
Advanced analytics	○	○	○	○	○	○	○	○

* 17. Do you agree with the following statements?

Using data analytics tools ...

	strongly disagree						strongly agree	n/a
... enables me to accomplish tasks **more quickly**.	○	○	○	○	○	○	○	○
... improves the **quality** of the work I do.	○	○	○	○	○	○	○	○
... I increase my chances of obtaining a **promotion** and/or **raise**.	○	○	○	○	○	○	○	○

* 18. Do you agree with the following statements?

	strongly disagree						strongly agree	n/a
I **intend to use** data analytics tools in the next FDD projects.	○	○	○	○	○	○	○	○
It is/was **easy** for me to **become skillful** at using data analytics tools.	○	○	○	○	○	○	○	○
I find data analytics tools **easy to use**.	○	○	○	○	○	○	○	○
Learning to operate data analytics tools is/was **easy** for me.	○	○	○	○	○	○	○	○
People who are important to me think that I **should use** data analytics tools.	○	○	○	○	○	○	○	○
People in my organization who use data analytics tools have a **high profile**.	○	○	○	○	○	○	○	○
I **predict I will use** data analytics tools in the next FDD projects.	○	○	○	○	○	○	○	○

* 19. Do you agree with the following statements?

	strongly disagree						strongly agree	n/a
The **senior management** has been **helpful** in the use of data analytics tools.								
I have the **resources** necessary to use data analytics tools.								
I have the **knowledge** necessary to use data analytics tools.								
Data analytics tools are **not compatible with other software** I use.								
Although it might be helpful, using data analytics tools is **certainly not compulsory** in my job.								
I **plan to use** data analytics tools in the next FDD projects.								

Previous Next

Data Analytics in the Financial Due Diligence (FDD)

6. Implications and trends

6 / 8 75%

* 20. In your opinion, how **likely** will the following **developments** occur within the next five to ten years?

	very unlikely				very likely	n/a
Full **automation** of the analyses frequently performed in an FDD						
Use of data from **global benchmarking database** from previous engagements						
Machine learning-based classification of items as normalizations or pro forma adjustments						
Predictive analytics to develop an alternative business plan						
Interactive **dashboards** as a supplement to the FDD final report						

* 21. Do you agree with the following statements?

Audit firms will ...

	strongly disagree				strongly agree	n/a
... **maximize efficiency gains** from data analytics through large-scale adoption, automation, and off-shoring.	◯	◯	◯	◯	◯	◯
... use data analytics (even) **more value- and insights-oriented** in the medium- to long-term.	◯	◯	◯	◯	◯	◯
... stronger bundle functional, technical, and industry competencies in **cross-functional teams**.	◯	◯	◯	◯	◯	◯
... move away from the bill-by-hour approach towards elements of **subscription models or value-based pricing**.	◯	◯	◯	◯	◯	◯

* 22. Do you agree with the following statements?

The FDD will be ...

	strongly disagree				strongly agree	n/a
... stronger **linked to other due diligence forms** through its increasing value orientation and a shared data model.	◯	◯	◯	◯	◯	◯
... stronger **integrated into the M&A process** and collaboration with other work streams will increase.	◯	◯	◯	◯	◯	◯

Previous Next

Data Analytics in the Financial Due Diligence
Research Project at the University of St. Gallen

University of St.Gallen
Institut für Finanzwissenschaft, Finanzrecht und Law and Economics

Data Analytics in the Financial Due Diligence (FDD)

7. Demographics

7 / 8 88%

* 23. Type of organization

◯ Big Four

◯ Next Ten

◯ Other (please specify)

* 24. Department

○ Transaction Services/Due Diligence

○ Deals Analytics/Technology

○ Other (please specify)

* 25. Rank

○ Partner

○ Director

○ Senior Manager

○ Manager

○ Senior Consultant

○ Consultant

○ Other (please specify)

26. Country of employment

○ Germany

○ Switzerland

○ Austria

○ Other (please specify)

27. Gender

○ Male

○ Female

28. Age

Years

Previous Next

Data Analytics in the Financial Due Diligence
Research Project at the University of St. Gallen

University of St.Gallen — Institut für Finanzwissenschaft, Finanzrecht und Law and Economics

Data Analytics in the Financial Due Diligence (FDD)

8. Questions and remarks

8 / 8 — 100%

29. Do you have questions, remarks, or additions?

As a thank you for your participation, I would like to send you the **exclusively prepared results of the study**. In addition, I am raffling an **Apple iPad** as well as **12 Amazon vouchers (50€ each)** among all study participants.

30. Please indicate whether you are interested and agree to the necessary storage of your personal data: I agree to the **storage/use of my personal data** ...

	yes	no
... in order to receive the **exclusively prepared study results**.	○	○
... in order to participate in the raffle of an **Apple iPad** and **12x 50€ Amazon vouchers**.	○	○

31. Personal contact details

Name (optional)

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Previous | Done

Source: Own illustration

Appendix 5: Summary statistics

Table A.3: Use of data analytics – Summary statistics of categorical variables

Variable	n	Frequencies (absolute)	Frequencies (relative)
Stimulating trends for data analytics			
Data availability	289	169	58.5%
Data granularity	289	143	49.5%
Standardization of data formats	289	113	39.1%
Access to the target's source systems	289	55	19.0%
Possibilities of data sharing	289	23	8.0%
Possibilities of data preparation/transformation	289	113	39.1%
Possibilities of data analysis	289	146	50.5%
Clients' requirements/expectations	289	61	21.1%
Usage of non-financial data from the target company			
Country data	289	91	31.5%
Customer data	289	185	64.0%
Operations data	289	88	30.4%
Product data	289	139	48.1%
Store data	289	95	32.9%
Staff/employee data	289	118	40.8%
Supplier data	289	76	26.3%
No use of non-financial data	289	7	2.4%
Usage of non-financial data from external sources			
Demographic data	289	113	39.1%
Geolocational/geospatial data	289	89	30.8%
Sensor/weather data	289	10	3.5%
Social media data	289	22	7.6%
Transactional/market data	289	179	61.9%
Website data	289	110	38.1%
No use of non-financial data	289	34	11.8%
Preferred data analytics tools[1]			
Alteryx Designer	277	182	65.7%
Customized self-developed tools	277	34	12.3%
MS Excel	277	200	72.2%
MS Excel Smart	277	54	19.5%
MS Excel Power Pivot	277	88	31.8%
MS Excel Power Query/Get & Transform	277	49	17.7%
MS Excel VBA (macros)	277	28	10.1%
MS Power BI	277	71	25.6%
Qlikview	277	9	3.2%
Statistical software (e.g., R, SPSS, Stata)	277	12	4.3%
Tableau	277	79	28.5%
Use of a data model (single version of the truth)			
Yes	277	201	72.6%
No	277	76	27.4%
Determinants of the use of data analytics in project situations			
Deal complexity	277	201	72.6%
Deal scope	277	202	72.9%
Compatibility with client's IT capabilities	277	70	25.3%
Time restrictions	277	119	43.0%
Client's demand for interim results	277	38	13.7%
Budget restrictions	277	116	41.9%
Availability of skilled resources	277	91	32.9%
Data availability	277	244	88.1%
Data variety	277	91	32.9%

Data veracity	277	63	22.7%
Profitability analyses benefitting from data analytics			
Cohort analysis	277	96	34.7%
Customer churn analysis	277	112	40.4%
Customer lifetime value (CLTV) analysis	277	54	19.5%
Identification of one-offs	277	59	21.3%
Price-volume analysis	277	183	66.1%
Raw material pass-through analysis	277	21	7.6%
Reconciliations	277	64	23.1%
Sum of the parts P&L	277	77	27.8%
Transaction effect analysis	277	29	10.5%
Translation effect/constant currency analysis	277	46	16.6%

Notes:
1) The frequency displays the sum of top 1, top 2, and top 3 listings of the corresponding items.

Source: Own illustration based on survey results

Table A.4: Use of data analytics – Summary statistics of continuous variables

Variable	n	Mean	Median	Std. deviation	Min.	Max.
Impact and suitability						
Impact	330	4.49	5	0.65	2	5
Suitability	320	4.16	4	0.79	1	5
Determinants of data availability and granularity						
Initiator	280	4.50	5	0.74	2	5
Negotiation situation	265	3.35	3	1.05	1	5
Target company size	285	3.89	4	1.02	1	5
Selling party	266	4.04	4	0.95	1	5
Public listing	252	3.05	3	1.22	1	5
Financial sponsor ownership	265	3.60	4	1.03	1	5
Sales fragmentation	254	3.05	3	1.10	1	5
Data culture	269	4.29	4	0.82	1	5
Usage of different data types						
Target-internal financial data	287	4.90	5	0.39	2	5
Target-internal non-financial data	285	3.94	4	0.84	1	5
Target-external financial data	286	3.05	3	1.04	1	5
Target-external non-financial data	286	2.87	3	1.02	1	5
Time shifts in data preparation and analysis						
Time shifts	270	4.13	4	1.03	1	5
Emerging trade-off	272	4.21	5	1.03	1	5
Use of data analytics across review areas						
Profitability analysis (incl. quality of earn.)	268	3.94	4	0.88	1	5
Balance sheet analysis	265	3.37	4	1.14	1	5
Cash flow analysis	265	3.13	3	1.12	1	5
Business plan validation	255	3.11	3	1.10	1	5
Future technological developments						
Full automation of key analyses	264	3.66	4	1.22	1	5
Global benchmarking database	264	3.89	4	1.06	1	5
Machine learning-based classification	265	3.65	4	1.08	1	5
Predictive analytics-based business plan	259	3.67	4	1.04	1	5
Interactive dashboards	262	4.55	5	0.75	1	5
Impact of data analytics on audit firms						
Maximization of efficiency gains	257	4.25	4	0.74	1	5
Shift towards value and insight-orientation	258	4.31	4	0.69	2	5
Use of cross-functional teams	257	4.08	4	0.83	1	5
Alternative pricing approaches	244	3.49	4	1.15	1	5
Impact of data analytics on FDD in the M&A process						
Increasing links to other due diligence forms	263	4.16	4	0.83	2	5
Increasing integration into M&A process	261	4.13	4	0.90	1	5

Source: Own illustration based on survey results

Appendix 6: Measurement model – Parameter estimates

Table A.5: Measurement model – Unstandardized parameter estimates

Variable	Expected sign	Unstd. coefficient	Std. error	z-value	p-value
Actual use (USE)					
USE_1[1]					
USE	+	1.0000[3]			
Constant	+	3.9944	0.1050	38.04	0.000****
Behavioral intention (BI)					
BI_1					
BI	+	1.0000[3]			
Constant	+	5.9133	0.0753	78.56	0.000****
BI_2					
BI	+	1.1295	0.0450	25.10	0.000****
Constant	+	5.7905	0.0816	70.93	0.000****
BI_3					
BI	+	1.1300	0.0502	22.52	0.000****
Constant	+	5.7501	0.0855	67.28	0.000****
Performance expectancy (PE)					
PE_1					
PE	+	1.0000[3]			
Constant	+	5.2849	0.0921	57.37	0.000****
PE_2					
PE	+	0.7230	0.0708	10.21	0.000****
Constant	+	5.7290	0.0700	81.81	0.000****
Effort expectancy (EE)					
EE_1					
EE	+	1.0000[3]			
Constant	+	4.6430	0.9693	47.90	0.000****
EE_2					
EE	+	0.9799	0.0431	22.72	0.000****
Constant	+	4.4579	0.0937	47.60	0.000****
EE_3					
EE	+	0.9439	0.0404	23.38	0.000****
Constant	+	4.6081	0.8945	51.52	0.000****
Social influence (SI)					
SI_1					
SI	+	1.0000[3]			
Constant	+	5.3339	0.0878	60.74	0.000****
SI_2					
SI	+	0.7299	0.0733	9.96	0.000****
Constant	+	5.2932	0.8964	59.05	0.000****
SI_3					
SI	+	0.8249	0.0993	8.30	0.000****
Constant	+	4.4463	0.1111	40.02	0.000****
Facilitating conditions (FC)					
FC_1					
FC	+	1.0000[3]			
Constant	+	5.0275	0.0993	50.63	0.000****
FC_2					
FC	+	1.3943	0.1019	13.69	0.000****
Constant	+	4.7354	0.1011	46.85	0.000****
FC_3[2]					
FC	+	0.7972	0.0864	9.23	0.000****
Constant	+	5.2107	0.0961	54.22	0.000****

Notes:
Error variances of the indicator variables, variances of the latent variables, and covariances between the latent variables are not displayed.
1) The item was requested on a scale from 0 to 100 and has been linearly transformed to a scale from 1 to 7.
2) The item refers to a negative-wording question and has therefore been reverse-coded.
3) The value is pre-determined to 1 since the item serves as the reference indicator. Consequently, no standard error and z-statistics are displayed.

Variables definition:
*, **, ***, **** indicate $p<0.1$, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.6: Measurement model – Standardized parameter estimates

Variable	Expected sign	Std. coefficient	Std. error	z-value	p-value
Actual use (USE)					
USE_1[1]					
USE	+	1.0000[3]	0.0000	$4.2e^{16}$	0.000****
Constant	+	2.3151	0.1166	19.85	0.000****
Behavioral intention (BI)					
BI_1					
BI	+	0.9050	0.0141	64.30	0.000****
Constant	+	4.8116	0.2186	22.01	0.000****
BI_2					
BI	+	0.9418	0.0107	88.10	0.000****
Constant	+	4.3410	0.1983	21.90	0.000****
BI_3					
BI	+	0.9002	0.0140	64.09	0.000****
Constant	+	4.1190	0.1904	21.63	0.000****
Performance expectancy (PE)					
PE_1					
PE	+	0.7929	0.0385	20.62	0.000****
Constant	+	3.5270	0.1679	21.01	0.000****
PE_2					
PE	+	0.7527	0.0394	19.11	0.000****
Constant	+	5.0198	0.2280	22.01	0.000****
Effort expectancy (EE)					
EE_1					
EE	+	0.9024	0.0145	62.02	0.000****
Constant	+	2.9578	0.1449	20.41	0.000****
EE_2					
EE	+	0.9153	0.0133	69.07	0.000****
Constant	+	2.9394	0.1445	20.35	0.000****
EE_3					
EE	+	0.9242	0.0124	74.25	0.000****
Constant	+	3.1852	0.1552	20.53	0.000****
Social influence (SI)					
SI_1					
SI	+	0.8504	0.0327	25.98	0.000****
Constant	+	3.7839	0.1815	20.85	0.000****
SI_2					
SI	+	0.6073	0.0459	13.23	0.000****
Constant	+	3.6743	0.1741	21.11	0.000****
SI_3					
SI	+	0.5542	0.0498	11.12	0.000****
Constant	+	2.4920	0.1284	19.41	0.000****
Facilitating conditions (FC)					
FC_1					
FC	+	0.7099	0.0345	20.60	0.000****
Constant	+	3.0969	0.1481	20.92	0.000****
FC_2					
FC	+	0.9710	0.0166	58.56	0.0000****
Constant	+	2.8616	0.1380	20.73	0.0000****
FC_3[2]					
FC	+	0.6058	0.0442	13.69	0.0000****
Constant	+	3.4359	0.1727	19.90	0.0000****

Notes:
Error variances of the indicator variables, variances of the latent variables, and covariances between the latent variables are not displayed. Variances of the latent variables are fixed to zero for the calculation of standardized coefficients.
1) The item was requested on a scale from 0 to 100 and has been linearly transformed to a scale from 1 to 7.
2) The item refers to a negative-wording question and has therefore been reverse-coded.
3) The value is pre-determined to 1 since the actual use (USE) construct represents a single-indicator latent variable for which the error variance is artificially fixed to zero for model identification purposes (i.e., it technically equals a manifest variable).

Variables definition:
*, **, ***, **** indicate $p<0.1$, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Appendix 7: Structural model – Parameter estimates

Table A.7: Structural model – Standardized parameter estimates

Variable	Expected sign	Std. coefficient	Std. error	z-value	p-value
Effects on behavioral intention (BI)					
H1: PE → BI	+	0.2813	0.0914	3.08	0.002***
H2: EE → BI	+	0.0294	0.0715	0.41	0.681
H3: SI → BI	+	0.6387	0.0892	7.16	0.000****
Effects on actual use (USE)					
H4: FC → USE	+	0.2161	0.0725	2.98	0.003***
H5: BI → USE	+	0.4659	0.0695	6.71	0.000****

Notes:
Variances of the latent variables and covariances between the latent variables are not displayed. Variances of the latent variables are fixed to zero for the calculation of standardized coefficients.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.8: Structural model – Standardized parameter estimates (GSANL subsample)

Variable	Expected sign	Std. coefficient	Std. error	z-value	p-value
Effects on behavioral intention (BI)					
H1: PE → BI	+	0.2223	0.1041	2.13	0.033**
H2: EE → BI	+	0.0618	0.0874	0.71	0.480
H3: SI → BI	+	0.6813	0.1119	6.09	0.000****
Effects on actual use (USE)					
H4: FC → USE	+	0.2093	0.0807	2.59	0.010**
H5: BI → USE	+	0.4348	0.0777	5.60	0.000****

Notes:
Variances of the latent variables and covariances between the latent variables are not displayed. Variances of the latent variables are fixed to zero for the calculation of standardized coefficients.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Appendix 8: Multi-group analysis of interaction effects

Table A.9: Analysis of the moderating effect of gender

(Pot.) moderated effect	Total sample	Group samples			Likelihood ratio test
	n=262 Unstd. coefficient	Females, n=61 Unstd. coefficient[0]	Males, n=201 Unstd. coefficient[1]	Mean diff. [0-1]	χ^2 (df)
H1a: PE → BI	0.3030***	0.2533*	0.3157***	-0.4679**	0.26 (1)
H2a: EE → BI	0.0245	-0.0593	0.0584	-0.1958	1.93 (1)
SI → BI	0.5668****	0.4256****	0.6116****	-0.4671**	2.80 (1)*
FC → USE	0.3372***	0.3301*	0.3393***	-0.1534	0.00 (1)

Notes:
For each potentially moderated effect, a model with measurement equivalence constraints and a parallel slopes assumption for all latent variables was tested against the almost identical model for which the parallel slopes assumption was released for the potentially moderated effect. Consequently, the likelihood ratio test that compares whether the models are significantly different always has one degree of freedom.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.10: Analysis of the moderating effect of age

(Pot.) moderated effect	Total sample	Group samples			Likelihood ratio test
	n=248 Unstd. coefficient	Young, n=114 Unstd. coefficient[0]	Old, n=134 Unstd. coefficient[1]	Mean diff. [0-1]	χ^2 (df)
H1b: PE → BI	0.2750**	0.2389*	0.3100**	-0.2119	0.61 (1)
H2b: EE → BI	-0.0226	-0.0762	0.0116	-0.6521****	1.41 (1)
SI → BI	0.6137****	0.4850***	0.6369****	-0.3000*	2.18 (1)
FC → USE	0.2935***	0.4090***	0.1720	-0.3284**	2.56 (1)

Notes:
For each potentially moderated effect, a model with measurement equivalence constraints and a parallel slopes assumption for all latent variables was tested against the almost identical model for which the parallel slopes assumption was released for the potentially moderated effect. Consequently, the likelihood ratio test that compares whether the models are significantly different always has one degree of freedom.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.11: Analysis of the moderating effect of hierarchy level (1/3)

(Pot.) moderated effect	Total sample	Group samples			Likelihood ratio test
	n=265 Unstd. coefficient	Junior, n=177 Unstd. coefficient[0]	Senior, n=88 Unstd. coefficient[1]	Mean diff. [0-1]	χ^2 (df)
H1c: PE → BI	0.2495***	0.2313**	0.2690***	-0.3118	0.17 (1)
H2c: EE → BI	0.0144	-0.0138	0.0689	-0.7415****	1.27 (1)
SI → BI	0.6037****	0.5735****	0.6668****	-0.1849	0.96 (1)
FC → USE	0.3386***	0.3607***	0.3001*	-0.4285***	0.14 (1)

Notes:
For each potentially moderated effect, a model with measurement equivalence constraints and a parallel slopes assumption for all latent variables was tested against the almost identical model for which the parallel slopes assumption was released for the potentially moderated effect. Consequently, the likelihood ratio test that compares whether the models are significantly different always has one degree of freedom.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.12: Analysis of the moderating effect of hierarchy level (2/3)

(Pot.) moderated effect	Total sample	Group samples			Likelihood ratio test
	n=248 Unstd. coefficient	Junior, n=177 Unstd. coefficient[0]	Senior, n=71 Unstd. coefficient[1]	Mean diff. [0-1]	χ^2 (df)
H1c: PE → BI	0.2221**	0.2056*	0.2416**	-0.3558*	0.13 (1)
H2c: EE → BI	0.0121	-0.0085	0.1073	-0.7910****	1.90 (1)
SI → BI	0.6258****	0.5865****	0.7130****	-0.3379	1.47 (1)
FC → USE	0.3775***	0.3683***	0.3995**	-0.4973***	0.03 (1)

Notes:
For each potentially moderated effect, a model with measurement equivalence constraints and a parallel slopes assumption for all latent variables was tested against the almost identical model for which the parallel slopes assumption was released for the potentially moderated effect. Consequently, the likelihood ratio test that compares whether the models are significantly different always has one degree of freedom.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.13: Analysis of the moderating effect of hierarchy level (3/3)

(Pot.) moderated effect	Total sample	Group samples			Likelihood ratio test
	n=265 Unstd. coefficient	Junior, n=194 Unstd. coefficient[0]	Senior, n=71 Unstd. coefficient[1]	Mean diff. [0-1]	χ^2 (df)
H1c: PE → BI	0.2361**	0.2236**	0.2521**	-0.3436	0.08 (1)
H2c: EE → BI	0.0107	-0.0059	0.1060	-0.7386****	1.83 (1)
SI → BI	0.6195****	0.5804****	0.7052****	-0.3794*	1.46 (1)
FC → USE[1]	0.3246***	-	-	-	-

Notes:
For each potentially moderated effect, a model with measurement equivalence constraints and a parallel slopes assumption for all latent variables was tested against the almost identical model for which the parallel slopes assumption was released for the potentially moderated effect. Consequently, the likelihood ratio test that compares whether the models are significantly different always has one degree of freedom.
1) The group model with a released parallel slopes assumption (and the minimization of its discrepancy function) could not be calculated by Stata v15.1.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.14: Analysis of the moderating effect of voluntariness

(Pot.) moderated effect	Total sample	Group samples			Likelihood ratio test
	n=264 Unstd. coefficient	Low, n=115 Unstd. coefficient[0]	High, n=149 Unstd. coefficient[1]	Mean diff. [0-1]	χ^2 (df)
PE → BI	0.2292**	0.1601	0.2982***	-0.3196*	2.22 (1)
EE → BI	-0.0036	-0.0355	0.0518	-0.2731	1.24 (1)
SI → BI[1]	0.6624****	-	-	-	-
FC → USE	0.3214***	0.4058***	0.2373*	-0.2019	1.10 (1)

Notes:
For each potentially moderated effect, a model with measurement equivalence constraints and a parallel slopes assumption for all latent variables was tested against the almost identical model for which the parallel slopes assumption was released for the potentially moderated effect. Consequently, the likelihood ratio test that compares whether the models are significantly different always has one degree of freedom.
1) The group model with a released parallel slopes assumption (and the minimization of its discrepancy function) could not be calculated by Stata v15.1.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

Table A.15: Analysis of the moderating effect of experience

(Pot.) moderated effect	Total sample	Group samples			Likelihood ratio test
	n=258 Unstd. coefficient	Low, n=139 Unstd. coefficient[0]	High, n=119 Unstd. coefficient[1]	Mean diff. [0-1]	χ^2 (df)
PE → BI	0.4031****	0.4172****	0.3704****	1.1159****	0.18 (1)
EE → BI	-0.0296	0.0727	-0.0928	1.4855****	4.05 (1)**
SI → BI	0.4892****	0.5150****	0.4345****	0.8834****	0.70 (1)
FC → USE	0.2124*	0.2547**	0.0967	1.1160****	0.74 (1)

Notes:
For each potentially moderated effect, a model with measurement equivalence constraints and a parallel slopes assumption for all latent variables was tested against the almost identical model for which the parallel slopes assumption was released for the potentially moderated effect. Consequently, the likelihood ratio test that compares whether the models are significantly different always has one degree of freedom.

Variables definition:
*, **, ***, **** indicate p<0.1, 0.05, 0.01, and 0.001 respectively

Source: Own illustration based on survey results

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Professional Experience

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Associate | Strategy Consulting	Jan 2017 – Jun 2018
A.T. Kearney	Zurich | CH
Summer Trainee | Strategy Consulting	Jan 2016 – Mar 2016
Stern Stewart & Co.	Munich | DE
Intern | Strategy Consulting	Jun 2015 – Aug 2015
KPMG	Dusseldorf | DE
Intern | Finance Advisory	Jun 2014 – Aug 2014
Horváth & Partners Management Consultants	Dusseldorf | DE
Intern | Controlling & Finance	Jan 2014 – Apr 2014
AGRO Holding	Bad Essen | DE
Intern | Group Controlling	Feb 2013 – Apr 2013

Education

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