Realizing Business Value Through Artificial Intelligence-Driven Analytics: Theoretical Foundation and Empirical Evidence

Inauguraldissertation

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Osnabrück, January 2022 Eduard Anton

Notes on the Structure of the Document

This cumulative dissertation is divided into two parts: Part A provides an introductory overview of the included research contributions that address the overarching research aim of the thesis. Part A is a standalone paper, which is structured and elaborated accordingly. Part B contains the research contributions on which Part A is based. Each contribution in Part B is a standalone paper and accordingly retains the content, structure, and formatting features (e.g., reference style) that are present in the original publications.

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Part A: Introductory Overview

List of Abbreviations

AI	Artificial intelligence
BDA	Big data analytics
BFSI	Banks, financial services, and insurance
BI	Business intelligence
COVID-19	Coronavirus disease 2019
fsQCA	Fuzzy set qualitative comparative analysis
IS	Information systems
IT	Information technology
MASEM	Meta analytic structural equation modeling
QCA	Qualitative comparative analysis
RBV	Resource-based view
TAM	Technology Acceptance Model
VHB	Verband der Hochschullehrer der Betriebswirtschaft
WKWI	Wissenschaftliche Kommission Wirtschaftsinformatik

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1 Introduction

The digitization of almost all areas of the economy and society directly entails generating an asset in vast quantities: data (Baesens *et al.*, 2016; Mikalef and Gupta, 2021). The economic potential of harnessing the informational value of these hundreds of created zettabytes was estimated at $215 billion in global revenue in 2021 (Statista, 2021). Consequently, companies in virtually all industries are investing in analytics capabilities to gain insights into data accumulated from various internal and external sources to support their decision making and derive business value (Chen *et al.*, 2012; Grover *et al.*, 2018). However, extracting insights from these complex and large datasets, often referred to as big data, requires organizations to handle the ramifications that arise from their volume, velocity, and variety (Grover *et al.*, 2018). The discipline that addresses mastering these challenges is big data analytics (BDA), which involves analytics services (e.g., visualizations, exploration, explanations, and predictions) enabled through various techniques (e.g., statistical, econometric, and computational) to support informed decision making (Goes, 2014). With the increasing computing power and algorithmic developments since the turn of the millennium, more advanced techniques have emerged in the realm of BDA, usually involving artificial intelligence (AI) (Rana *et al.*, 2021).

The term AI was first coined at a Dartmouth conference in 1956 as "the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy *et al.*, 1955, p. 2). Since then, a wide range of technologies and algorithms have adopted the label of AI by simulating such "intelligence," constrained by the computational and programming limitations of their respective period (Benbya *et al.*, 2021; Russel and Norvig, 1995). Berente et al. (2021) interpret this evolution of AI as not being a particular technology or algorithm but rather an evolving process of computational capabilities that exploit present-day technological realities. This dissertation adopts this notion and defines AI "as the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems" (Berente *et al.*, 2021, p. 1435). The focus specifically lies on the contemporary frontier of the converging relationship between AI and big data, which stems both from the symbiotic relationship of AI using large datasets to train its models and from AI deciphering the explanatory value of structural data by recognizing patterns using machine learning techniques or processing unstructured data using natural language processing (Berente *et al.*, 2021; Mikalef and Gupta, 2021; Rana *et al.*, 2021).

In a comprehensive study shedding light on AI use in practice, Chui et al. (2018) show that two-thirds of AI use cases involve improving existing analytics use cases. However, unlike other BDA techniques, the capabilities of AI go beyond preparing data and creating the information basis for data-driven decisions in regard to various value targets (e.g., business process improvement, consumer experience, products, and service innovation) (Grover *et al.*, 2018). While AI can support analytics processes through its automation and augmentation capabilities (Oesterreich *et al.*, 2021; Prat, 2019), AI systems can also become an active part of the value chain by assuming repetitive tasks or augmenting the existing workforce (Bughin *et al.*, 2017).

Thus, AI represents a hybrid information technology (IT) resource that combines the characteristics and strengths of humans and IT artifacts (Anton *et al.*, 2020; Plastino and Purdy, 2018). Nevertheless, employees could be threatened by and sceptic about such a sophisticated technology (Makarius *et al.*, 2020). AI implementation raises specific challenges related to factors such as security and ethics, especially since AI-based models are highly data dependent and thus prone to security risks and biases, necessitating accountability mechanisms and trust building (Berente *et al.*, 2021; Rana *et al.*, 2021). As a result, the complexity of the sociotechnical system is increasing and must be managed to reap the business value of AI (Baird and Maruping, 2021; Berente *et al.*, 2021; Makarius *et al.*, 2020). Accordingly, to integrate AI into people's work environments so that they can collaborate effectively, businesses must do more than merely provide tangible resources (e.g., infrastructure, data, and algorithms); rather, a significant organizational effort is required to orchestrate the tangible, intangible, and human resources in the context of the sociotechnical environment (Berente *et al.*, 2021; Enholm *et al.*, 2021; Mikalef and Gupta, 2021). Many businesses fail in these efforts because there is a lack of knowledge about how to build AI capabilities (Mikalef and Gupta, 2021) or understanding of AI adoption and value-creating mechanisms (Borges *et al.*, 2021; Enholm *et al.*, 2021; Makarius *et al.*, 2020).

1.1 Aim

The overarching aim of this cumulative dissertation is to provide theoretical underpinnings for and empirical evidence of the mechanisms necessary to build and realize AI capabilities for data-driven value creation in an organizational context. As mentioned previously, this dissertation considers AI-driven analytics, exploring its potential within the analytics cycle as well as its active role in the value creation process. Research within the information systems (IS) field has previously examined the necessary capabilities and value creation mechanisms related to BDA (Grover *et al.*, 2018; Mikalef and Krogstie, 2020), but as Krishnamoorthi and Mathew (2018, p. 643) point out, there is a need to understand "how the nuances of value creation mechanism[s] vary with the type of organizations and the analytics maturity of organizations." Therefore, this work contributes to existing BDA research by enhancing the understanding of the capability building and realization process for more advanced analytics by illuminating the dynamics associated with AI adoption in sociotechnical systems. This focus addresses a research gap with little theoretical foundation in IS research (Borges *et al.*, 2021; Enholm *et al.*, 2021; Makarius *et al.*, 2020; Mikalef and Gupta, 2021; Schmidt *et al.*, 2020) that can provide directions for "the core areas that organizations should steer their focus toward when deploying AI initiatives and provide a notion upon which to gauge the potential business value and mechanisms of value creation" (Mikalef and Gupta, 2021, p. 4). In addition, the dissertation heeds recent calls for studying the interactions between humans and AI artifacts (Baird and Maruping, 2021; Makarius *et al.*, 2020). Therefore, this thesis endeavors to answer the following research question:

Which capabilities are necessary to effectively leverage AI-driven analytics and what value-creating mechanisms can they enable?

To attain the overarching research objective, this cumulative dissertation reports on eight individual research papers embedded in a framework that builds on the BDA-related business value model of Grover et al. (2018). The research contributions draw on a wide range of qualitative and quantitative methods, addressing behavioral and design-oriented IS research questions, and thus providing a theoretical and empirical foundation for addressing the research goal.

1.2 Structure of the Work

The remainder of this cumulative dissertation is structured as follows: Chapter 2 addresses the research design, which includes introducing the research contributions, the research framework and approach, and the methodological spectrum of this cumulative dissertation. In Chapter 3, the results of this dissertation are summarized. The findings are not presented in a chronological or specific order but are embedded in various research themes according to the research framework. To avoid redundancy, the methodological approach, theories, and results of the eight research contributions are not described in detail; rather, the focus lies on the main findings. For more details, please refer to the full contributions in Part B. The findings are summarized in an explanatory model in Chapter 4 and discussed in terms of their theoretical and practical implications and limitations. Chapter 5 concludes the introductory overview of this dissertation.

2 Research Design

The research question is addressed by eight individual research contributions. Section 2.1 introduces these papers, which are subsequently mapped into the research framework underpinning this thesis in Section 2.2. Finally, Section 2.3 outlines the dissertation's approach to answering the research question, thereby elaborating on the methodological spectrum.

2.1 Selection of the Research Contributions

Table 1 lists the publications included in this cumulative dissertation. These eight papers were published in leading and internationally renowned journals (**Papers V** and **VIII**) and conferences (**Papers I–IV**, **VI**, and **VII**) related to the IS field, all of which underwent a double-blind peer review process. Other papers have been published by the author of this work that are outside the scope of this dissertation but which contributed to the foundations of the research contained in this thesis.

To indicate the quality of publication sources, scholars often use journal and conference rankings. The rationale behind such rankings is that the higher a source is ranked, the more it is expected to feature articles of a sophisticated quality that impact research and practice (Lowry *et al.*, 2013). This dissertation relies on the following two rankings to assess the publication sources of the published papers:

- *VHB JOURQUAL3* (Verband der Hochschullehrer für Betriebswirtschaftslehre – Journal Quality Index 3; English translation: German Academic Association for Business Research) (VHB e.V., 2021).
- *WKWI* (Wissenschaftliche Kommission Wirtschaftsinformatik – Orientierungsliste 2008; English translation: Scientific Commission Information Systems – Guidance List 2008) (Heinzl, 2008).

These expert-based rankings assign a score from A to D to the publication sources, where A is the highest and D is the lowest score. According to the WKWI ranking, five of the eight presented papers were published in conferences ranked A, two of the papers were published in conferences ranked B, and one paper was published in a journal that focuses on innovation management and is not WKWI ranked. The VHB JOURQUAL3 ranking of the same publication sources awards one A, three B, and four C ratings.

Table 1 Selection of the Research Contributions

<table>
<tr><th rowspan="2">ID</th><th rowspan="2">Bibliographic Information</th><th colspan="2">†Ranking</th></tr>
<tr><th>VHB</th><th>WKWI</th></tr>
<tr><td rowspan="2">I</td><td rowspan="2">Schuir, J., Brinkhege, R., Anton, E., Oesterreich, T. D., Meier, P., and Teuteberg, F. (2021): Augmenting Humans in the Loop: Towards an Augmented Reality Object Labeling Application for Crowdsourcing Communities; in: Proceedings of the 16th International Conference on Wirtschaftsinformatik (WI 2021), Essen, Germany.[*0 *I]</td><td colspan="2">WI (Conference)</td></tr>
<tr><td>C</td><td>A</td></tr>
<tr><td rowspan="2">II</td><td rowspan="2">Anton, E., Behne, A., and Teuteberg, F. (2020): The Humans Behind Artificial Intelligence – An Operationalisation of AI Competencies; in: Twenty-Eighth European Conference on Information Systems (ECIS 2020), A Virtual AIS Conference.[*0 *II]</td><td colspan="2">ECIS (Conference)</td></tr>
<tr><td>B</td><td>A</td></tr>
<tr><td rowspan="2">§III</td><td rowspan="2">Anton, E., Oesterreich, T. D., and Teuteberg, F. (2021): Understanding the Operational Value of Big Data Analytics Capabilities for Firm Performance: A Meta-Analytic Structural Equation Modeling Approach; in: Forty-Second International Conference on Information Systems (ICIS 2021), Austin, USA.[*0 *III]</td><td colspan="2">ICIS (Conference)</td></tr>
<tr><td>A</td><td>A</td></tr>
<tr><td rowspan="2">IV</td><td rowspan="2">Oesterreich, T. D., Anton, E., and Xu, F. (2021): Augmenting the Future: An Exploratory Analysis of the Main Resources, Use Cases, and Implications of Augmented Analytics; in: Twenty-Ninth European Conference on Information Systems (ECIS 2021), A Virtual AIS Conference.[*0 *IV]</td><td colspan="2">ECIS (Conference)</td></tr>
<tr><td>B</td><td>A</td></tr>
<tr><td rowspan="2">V</td><td rowspan="2">Anton, E., Oesterreich, T. D., Schuir, J., Protz, L., and Teuteberg, F. (2021): A Business Model Taxonomy for Start-Ups in the Electric Power Industry – The Electrifying Effect of Artificial Intelligence on Business Model Innovation; International Journal of Innovation and Technology Management (IJITM), Vol. 18, No. 03, 2150004.[*0 *V]</td><td colspan="2">IJITM (Journal)</td></tr>
<tr><td>‡C</td><td>n.r.</td></tr>
<tr><td rowspan="2">VI</td><td rowspan="2">Anton, E., Kus, K., and Teuteberg, F. (2021): Is Ethics Really Such a Big Deal? The Influence of Perceived Usefulness of AI-Based Surveillance Technology on Ethical Decision-Making in Scenarios of Public Surveillance; in: Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS-54).[*0 *VI]</td><td colspan="2">HICSS (Conference)</td></tr>
<tr><td>C</td><td>B</td></tr>
<tr><td rowspan="2">VII</td><td rowspan="2">Anton, E., Oesterreich, T. D., Schuir, J., and Teuteberg, F. (2022): Painting A Holistic Picture of Trust in and Adoption of Conversational Agents: A Meta-Analytic Structural Equation Modeling Approach; to appear in: Proceedings of the 55th Hawaii International Conference on System Sciences (HICSS-55).[*0 *VII]</td><td colspan="2">HICSS (Conference)</td></tr>
<tr><td>C</td><td>B</td></tr>
<tr><td rowspan="2">VIII</td><td rowspan="2">Anton, E., Oesterreich, T. D., and Teuteberg, F. (2022): The Property of Being Causal – The Conduct of Qualitative Comparative Analysis in Information Systems Research; Information & Management, Vol. 59, No. 3, 103619.[*0 *VIII]</td><td colspan="2">I & M (Journal)</td></tr>
<tr><td>B</td><td>A</td></tr>
</table>

Comments

[*0] Prof. Dr Frank Teuteberg critically reflected on the content and methodological orientation in all contributions.

[*I] The author of this dissertation contributed to drafting the introduction and description of the artifact. Mr. Julian Schuir developed the idea of the article, conducted the literature review along with the market analysis, developed the design knowledge, and analyzed the evaluation results. Mr. René Brinkhege implemented the system. Dr. Thuy Duong Oesterreich contributed to drafting the implications. Dr. Pascal Meier reflected on the methodological orientation.

[*II] Ms. Alina Behne provided assistance during the literature review and preparation of the appendix.

[*III] Dr. Thuy Duong Oesterreich worked in equal parts on this contribution.

[*IV] Dr. Thuy Duong Oesterreich worked in equal parts on this contribution. Mr. Feipeng Xu supported the data gathering and analysis.

[*V] The author of this dissertation developed the idea of the article as well as the taxonomy, including the corresponding methodological procedures. Dr. Thuy Duong Oesterreich wrote the discussion of this work. Mr. Julian Schuir contributed to the literature review and description of the taxonomy. Ms. Leslie Protz gathered the data.

[*VI] Mr. Kevin Kus made a noteworthy contribution to the theoretical background of this article.

[*VII] The author of this dissertation developed the idea of the article, performed the methodological procedures, and wrote all sections that were not drafted by the co-authors. Dr. Thuy Duong Oesterreich contributed to the drafting of the research methodology in terms of literature selection and coding and worked in equal parts on the discussion. Mr. Julian Schuir contributed to the drafting of the theoretical background.

[*VIII] Dr. Thuy Duong Oesterreich worked in equal parts on this contribution.

† The quality of the publication sources was evaluated using the following two rankings (from A to D, with A being the highest and D being the lowest ranking; n.r. = not ranked):

- VHB: Verband der Hochschullehrer für Betriebswirtschaftslehre (English translation: German Academic Association for Business Research) – Journal Quality Index 3 (VHB e.V., 2021).
- WKWI: Wissenschaftliche Kommission Wirtschaftsinformatik – Orientierungsliste 2008 (English translation: Scientific Commission Information Systems – Guidance List 2008) (Heinzl, 2008).

‡ Based on the subranking "Technology, Innovation and Entrepreneurship" (all other VHB JOURQUAL 3 assessments are based on the subranking "Business and Information Systems Engineering").

§ This paper was awarded Best Paper in the *Governance, Strategy and Value of IS* track and nominated for the Best Overall Conference Paper Award at ICIS2021

2.2 Framework of the Research Contributions

Figure 1 depicts the guiding framework for the research of this dissertation. It is grounded in competence-based theories, such as the resource-based view (RBV) of the firm (Barney, 1991; Drnevich and Croson, 2013) and process-oriented IT business value models (Grover *et al.*, 2018; Melville *et al.*, 2004; Schryen, 2013). The RBV posits that differences in firm performance are a result of the variance in the distribution of valuable resources (Drnevich and Croson, 2013). In this context, resources can be defined "as assets and capabilities that are available and useful in detecting and responding to market opportunities and threats" (Wade and Hulland, 2004, p. 109). In particular, resources that are valuable, rare, non-imitable, and non-substitutable contribute to competitive advantage as argued by Barney (1991). However, it is debatable whether a competitive advantage can be achieved by merely investing technological resources (Carr, 2003) because if, for example, data are evaluated as a technological asset based on Barney's (1991) criteria, the conclusion is quickly reached that the criteria are not met (e.g., data are not scarce within the concept of big data). Therefore, to grasp the business value of technological investments and artifacts, researchers such as Melville et al. (2004) or Schryen (2013) have complemented to the tenet of the RBV by shedding light on the utilization mechanisms of resources. This approach has led to explanatory process models that consider IT resources in a bundle with other technical, human, and organizational resources that collectively enable or support business processes that can then impact firm performance (Melville *et al.*, 2004; Schryen, 2013).

Research that addresses the capabilities and business value of BDA (Abbasi *et al.*, 2016; Gupta and George, 2016; Krishnamoorthi and Mathew, 2018), AI (Mikalef *et al.*, 2019; Mikalef and Gupta, 2021), or the combination of both (Rana *et al.*, 2021) usually draws upon this background for their conceptual or empirical approaches. Grover et al. (2018) also build on the RBV and IT business value models to introduce capability building and realization processes to explicate BDA-enabled business value. According to this model, the process of *building capabilities* begins with infrastructural prerequisites such as big data assets, analytics portfolio, and human talent required to develop and build capabilities to integrate, disseminate, explore, and analyze big data. The *capability realization* process leverages established capabilities to create impact through value creation mechanisms (e.g., transparency, access, and prediction) for specific value targets (e.g., organizational performance, service and product innovation, consumer experience, and market enhancement). During the process of *value manifestation*, the conversion of BDA capabilities to business value is moderated by various contextual factors, such as trust or ethical aspects (Grover *et al.*, 2018).

This dissertation adopts Grover et al.'s (2018) model as a suitable starting point to study the peculiarities associated with the integration and adoption of AI-driven analytics. **Papers I** and **II** address the *capability building* process by focusing on data assets and AI preprocessing (Schuir et al., 2021) operationalizing technical and managerial AI capabilities (Anton et al., 2020), respectively. **Papers III–V** focus on *capability realization*. **Paper III** provides a better understanding of how capabilities translate into business value (Anton, Oesterreich and

Teuteberg, 2021), **Paper IV** addresses the main resources, use cases, and implications of augmented analytics (i.e., AI-based analytics) (Oesterreich *et al.*, 2021), and **Paper V** covers AI-driven business model innovations using the electric power industry as an example (Anton, Oesterreich, Schuir, *et al.*, 2021). **Paper IV** also tackles infrastructural aspects and the capabilities necessary for AI-based analytics. As the advent of AI challenges adoption processes in sociotechnical systems (Baird and Maruping, 2021; Berente *et al.*, 2021; Makarius *et al.*, 2020), the **Papers VI** and **VII** examine contextual enablers, focusing on ethics (Anton, Kus, *et al.*, 2021) and trust (Anton, Oesterreich, Schuir, *et al.*, 2022), that affect AI adoption and thus the conversion into business value during the *value manifestation* process.

Paper **VIII** is unrelated to the presented business value framework, but presents essential methodological foundations for conducting qualitative comparative analysis (QCA) studies, the recommendations of which are taken up in **Paper VI**, which employs QCA.

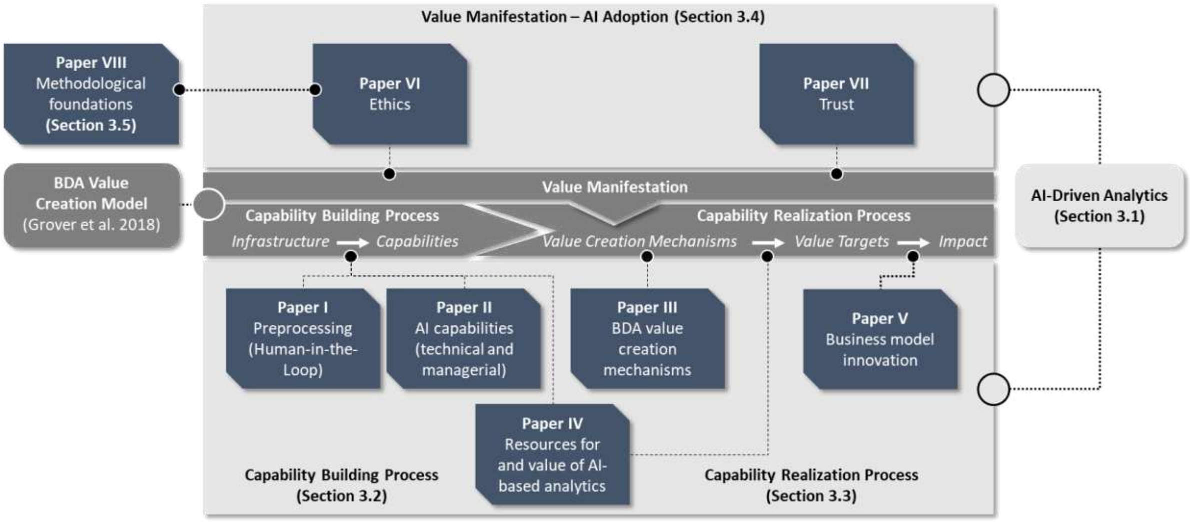


Figure 1 Research Framework of the Research Contributions

2.3 Research Approach and Spectrum of Applied Methods

With the overarching goal of understanding how AI-driven analytics can add value to organizations, this dissertation addresses the core aim of the IS discipline, which is “[t]o understand and improve the ways people create value with information” (Nunamaker, Jr. and Briggs, 2011, p. 2). With this purpose in mind, Nunamaker and Briggs (2011, p. 3) argue that pursuing IS research entails understanding “how to architect and adapt information systems to gain and sustain this value.” Therefore, the work of IS researchers entails elucidating various technical, economic, social, and design aspects related to different intradisciplinary streams to capture the broad scope of the discipline, namely behavioral IS research, organizational IS research, IS economics, and design science (Goes, 2013). In particular, two paradigms with their associated theories and methods permeate the literature: the *behavioral science paradigm*, which encompasses research that “explain[s] or predict[s] organizational and human phenomena surrounding the analysis, design, implementation, management, and use of information systems” and the *design science paradigm*, which embraces research that “create[s] innovations that define the ideas, practices, technical capabilities, and products through which the analysis, design, implementation, management, and use of information systems can be effectively and efficiently accomplished" (Hevner *et al.*, 2004, p. 76).

As indicated in Chapter 1, the use of AI as a hybrid resource goes beyond technical facets; AI-driven analytics is accompanied by multidimensional research problems arising from the entirely new dynamics in sociotechnical systems (Enholm *et al.*, 2021). Hence, this cumulative dissertation draws on the paradigm of design science and behavioral science, encompassing multiple methodologies that blend interpretivist and positivist perspectives. This is operationalized by a spectrum of methods in order to follow a pluralistic approach that can enrich multidimensional research and increase the reliability of the results (Goes, 2013; Mingers, 2001). At the level of the individual research contributions, **Paper I** can be assigned to the design science paradigm and **Papers II–VII** to the behavioral science paradigm, although this classification should not be interpreted absolutely in silos separated from each other, as the respective papers contain elements of both paradigms. **Paper VIII** is a methodology paper that outlines the conduct of QCA in the IS literature. As such, the paper cannot be assigned to one of the paradigms; rather, the study addresses the broad applicability of the methodology, which can be used for both behavioral and design science.

Table 2 Pluralist Approach of the Cumulative Dissertation

Spectrum of Methods (References)		I	II	III	IV	V	VI	VII	VIII
Qualitative	Literature review (vom Brocke *et al.*, 2009)	X	X	X	X	X	X	X	X
	Prototyping (Hevner *et al.*, 2004)	X							
	Focus group (Morgan, 1997)	X							
	Qualitative content analysis (Bandara *et al.*, 2015)		X		X				
	Expert interviews (Gläser and Laudel, 2010)					X			
Quantitative	Survey (Mayring, 2002)	X					X		
	Meta-analytic structural equation modeling (Cheung, 2015)			X				X	
	Meta-analysis (Borenstein *et al.*, 2009)			X				X	
	Structural equation modeling (Schumacker and Lomax, 2016)			X				X	
	Cluster analysis (Punj and Stewart, 1983)					X			
	Quantitative content analysis (Sidorova *et al.*, 2008)		X		X				
Qualitative and quantitative	Qualitative comparative analysis (Schneider and Wagemann, 2012)						X		X
	Taxonomy development (Nickerson *et al.*, 2013)					X			
Theoretical foundations I: Justificatory knowledge (Gregor and Hevner, 2013); II: RBV (Barney, 1991), IT business value model (Melville et al., 2004); III: RBV (Barney, 1991), IT business value model (Drnevich and Croson, 2013; Melville et al., 2004); IV: IT business value model (Melville et al., 2004; Schryen, 2013); V: Business model research (e.g., Baden-Fuller and Haefliger, 2013; Teece, 2010); VI: Issue-contingent model (Jones, 1991), Technology acceptance model (Davis, 1989); VII: Technology acceptance model (Davis, 1989), Trust technology acceptance model (Benbasat and Wang, 2005); VIII: Multiplicity framework (Park, Fiss, *et al.*, 2020).									

The methodological foundation of the cumulative dissertation can be described as mixed methods, as the qualitative and quantitative spectrum of methods are combined within a single research design (Venkatesh *et al.*, 2013). This is also evident within the individual papers, where mixed methods are used to triangulate findings, especially in **Papers II** and **IV**; apply qualitative approaches to develop research designs for further quantitative inquiry, especially in **Papers III** and **VII**; or, as in **Papers V** and **VI**, engage in "different methods for different inquiry components to expand the depth and breadth of the research" (Ågerfalk, 2013, p. 252). **Paper VIII** undertakes a systematic literature review of how QCA research has been conducted in IS literature and thereby describes the QCA methodology.

Table 2 provides an overview of the range of qualitative and quantitative methods applied and the underlying theoretical foundations exploited for deductive approaches and drawn upon to apply inductive reasoning to the results. Readers can find detailed information and procedural specifications on the individual methods in **Papers I–VIII**.

3 Summary of the Research Results

The results of the eight individual contributions are not presented individually but are embedded within the presented research framework in terms of the technological focus of AI-driven analytics (Section 3.1), capability building (Section 3.2), capability realization (Section 3.3), value manifestation, i.e., AI adoption (Section 3.4), and methodological foundations (Section 3.5).

3.1 Artificial Intelligence-Driven Analytics

In Chapter 1, the umbrella term AI is narrowed down to the frontier of computational advancements in data processing and analysis that enhances and complements BDA (Rana *et al.*, 2021). This section further specifies this definition to the technological scope considered in this cumulative dissertation. Figure 2 depicts the areas covered by the individual contributions on which the results of this cumulative dissertation are based. This technological scope is by no means an exhaustive overview of the capacities of AI[1], but it does encompass the main areas of AI use, namely automation and augmentation (Enholm *et al.*, 2021), and provides a basis for understanding the AI frontier in the analytics realm.

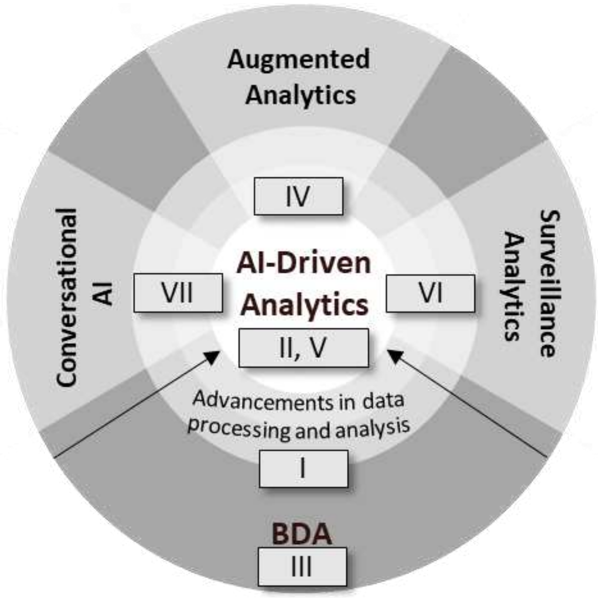


Figure 2 Technological Scope of the Research Contributions (Papers I–VII)

Paper III focuses on BDA, which similarly to AI, is a collection of technologies and techniques that represent a frontier of a technological pre-conception, that of business intelligence (BI). BI can be defined as, "a system comprised of both technical and organizational elements that presents its users with historical information for analysis to enable effective decision making and management support, with the overall purpose of increasing organizational performance" (Işik *et al.*, 2013, pp. 13–14). Goes (2014) describes BDA as a sophisticated area of BI that addresses

[1] See, for example, Benbya et al. (2021) for a list of AI types and technologies from a theoretical perspective and Bawack et al. (2019) from a practical view.

the back end of the intelligence chain (i.e., data→information→knowledge→intelligence) and enhances historical intelligence with real-time insights. To operationalize this, Goes' (2014) BDA taxonomy lists statistics, econometrics, computation, linguistics, optimization, simulation, and machine learning which enable predictive, explanatory, explorative, and visualizing analytics, forming this frontier. These techniques, such as machine learning and linguistics, are also typical in the AI conversation (Bawack *et al.*, 2019; Benbya *et al.*, 2021), which illustrates that there are no clear boundaries where one concept begins and the other ends. Accordingly, boundaries are defined by researchers and practitioners. Often the crucial aspect for moving towards AI-driven analytics is the reference to capabilities that exhibit similarities to human intelligence (Rana *et al.*, 2021).

Papers II and **V** adopt such an intelligence frame to define AI-driven analytics, since AI is studied in a broad sense within these contributions. However, the analytical solution space addressed by AI capabilities is mostly limited to a narrow use case (referred to as weak AI) because a general-purpose intelligence (known as strong AI) that can simulate the breadth of human's capabilities is currently far from existing (Benbya *et al.*, 2021). For a comprehensive literature review of the application areas of weak AI in the realm of decision support and advanced analytics, see the work of Borges et al. (2021).

The other research contributions of this dissertation take a more specific and functional view on AI-driven analytics that support data analysis or decision making, addressing augmented analytics (**Paper IV**), algorithmic AI (**Paper I**), surveillance analytics (**Paper VI**), and conversational AI (**Paper VII**).

Paper IV delves into augmented analytics, that is, "BDA enabled by artificial intelligence" (Oesterreich *et al.*, 2021, p. 1), showing that the two concepts BDA and AI are complementary. **Paper IV** elaborates that augmented analytics primarily refers to using AI to automate or augment activities in the analytics cycle (cf. Figure 3). The analytics cycle includes high-level processes that are typically conducted in data science engagements (Prat, 2019). The cycle begins by delving into the business model, processes, and other organizational and project-related aspects to understand the targeted problem space or business opportunity. The next process includes data preparation, which summarizes all activities related to the collection and streaming of data from various sources and pre-processing. After this process, data analysis steps are conducted, which encompass modeling the appropriate solution to be deployed in the subsequent phase. Based on the model deliverables, management can make informed decisions that are translated into actions, based on which new problems or opportunities for the business can be identified in the monitoring phase. **Paper IV** emphasizes that AI is not just a technique or algorithm used in modeling (i.e., in the data analysis process), but rather a set of tools that augment or substitute human activities in the analytics cycle.

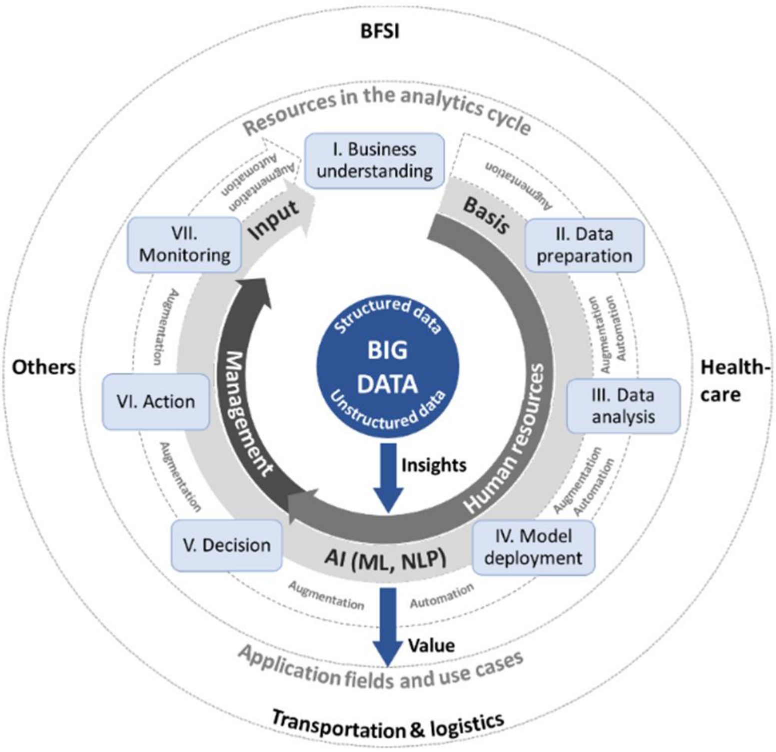


Figure 3 Augmented Analytics Framework (Oesterreich *et al.*, 2021, p. 11)

The key techniques operationalizing AI constitute machine learning and natural language processing. Machine learning generally includes clustering, classification, and regression algorithms used for pattern recognition in structural data to enable predictive analytics in productive data that share the same features as the data on which the employed algorithm was first trained (Oesterreich *et al.*, 2021; Russel and Norvig, 1995). Natural language processing describes algorithms that make it possible to understand unstructured data, such as text and speech, and to decode them syntactically and semantically with regard to their informational value. Such algorithms enable the streamlining and automation of preprocessing and modeling in particular (Oesterreich *et al.*, 2021).

Paper I demonstrates how such a streamlined data processing pipeline could be designed by developing a dedicated artifact for supporting the process. The technological focus within this contribution lies on convolutional neural networks, which are commonly used for image classification and typically subsumed under algorithmic AI (Benbya *et al.*, 2021; Schuir *et al.*, 2021).

AI-based surveillance analytics is a functional area considered in **Paper VI** and is typically operationalized by deep learning techniques, such as deep convolutional networks (Wang *et al.*, 2017). These systems are often employed to analyze video footage in real time and match it with biometric or other unstructured data, such as social media content, to mitigate criminal activity and increase security. **Paper VI** examines this realm of analytics in the public domain in the context of ethical aspects as they relate to the dichotomy between security and privacy (Anton, Kus, *et al.*, 2021).

The functional focus area of **Paper VII** is conversational AI, which is defined as "the general capability of computers to understand and respond with natural human language as it is written or spoken” (Benbya *et al.*, 2021, p. 302). Conversational AI is generally operationalized by voice- or text-based bots employing collections of algorithms related to natural language processing and understanding. The data processing possibilities enabled by these bots are broad and promise real time data analysis of inquiries or unstructured data that previously required human agents, thus offering potential savings in staff and costs. **Paper VII** highlights this AI arena in the context of trust and adoption (Anton, Oesterreich, Schuir, *et al.*, 2022).

The depicted functional domains are not detached from each other. For example, conversational AI techniques are used in augmented analytics, such as in SAP’s Smart Discovery, where natural language processing algorithms are employed to understand user questions, identify the required intent, and return data insights based on visualizations (Oesterreich *et al.*, 2021). However, by identifying patterns in large datasets or analyzing unstructured data, AI-driven analytics can not only enable search-based analytics, as is primarily the case in BI and BDA solutions, but can also provide users with insights they were not looking for or did not anticipate (Zinsmeister *et al.*, 2019).

3.2 Capability Building Process

The technological dimension of this cumulative dissertation is the subject of capability building at the organizational level. With such capabilities organizations can “use data, methods, processes and people in a way that creates new possibilities for automation, decision making, collaboration, etc. that would not be possible by conventional means” (Schmidt *et al.*, 2020, p. 3). Thus, AI capability at an organizational level subsumes the activities to effectively operationalize AI resources within the sociotechnical system. The importance of the sociotechnical system in the capability building process is confirmed by the frequency and network analysis in Figure 4, which highlights the relationship between technical, structural, and social components in the context of AI-based analytics (Oesterreich *et al.*, 2021).

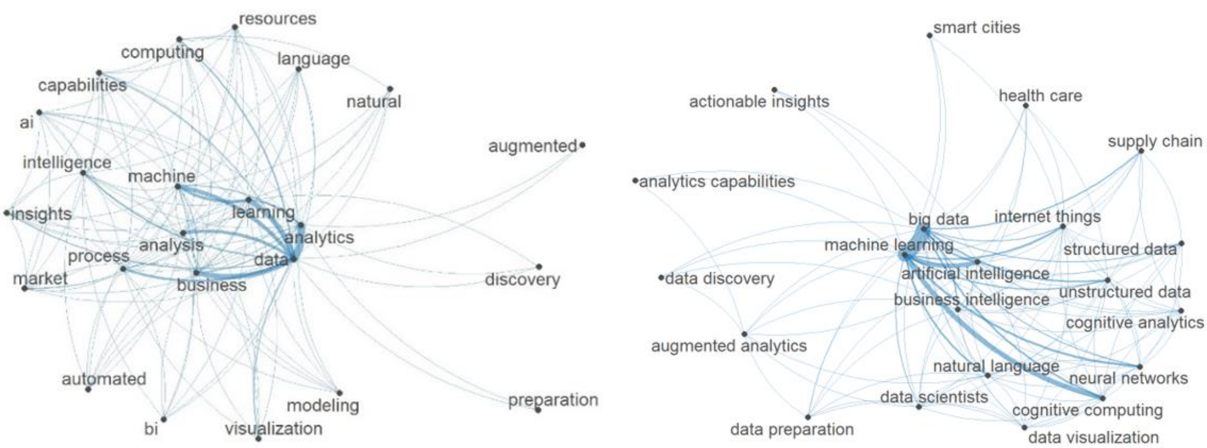


Figure 4 Relationships Between the Most Frequent Unigrams and Bigrams (Based on a Text Corpus of 350 AI-Related Studies) (Oesterreich *et al.*, 2021, p. 4)

Consistent with the RBV, IS literature points to technological, human, and organizational resources that must be acquired, managed, and orchestrated (Enholm *et al.*, 2021; Mikalef and

Gupta, 2021; Niehaus and Wiesche, 2021). Initially, these categories of tangible and intangible resources appear similar in the context of generating business value in other frontiers, for instance in the context of BDA (e.g., Grover *et al.*, 2018; Mikalef and Krogstie, 2020). Such an impression is created by the lack of operationalization of what these resource categories mean and how they should be deployed to create business value; instead, trendy capability terms, such as the necessary "digital skills," are mentioned in discussions on effective AI use (Anton *et al.*, 2020). Given, for example, that "digital skills" are always needed in today's business and IT landscape, such a high-level view is insufficient for understanding capability building. A more in-depth analysis is needed to emphasize the differences between concepts such as BDA and AI-driven analytics. Therefore, **Papers II** and **IV** pose the following research questions to operationalize AI capabilities and highlight differences to the BDA frontier:

(i) *Which competencies are required on an individual level for leveraging AI in organizations effectively?*[2]

(ii) *To what extent does the role of technological and human resources as well as management capabilities change in the augmented analytics concept?*[3]

Papers II and **IV** address these research questions through qualitative and quantitative content analyses in each study. **Paper II** examines the theoretical perspective by analyzing and coding 49 studies dealing with AI resources and capabilities. For the practical perspective on AI capabilities, 9,247 job advertisements from the platform Indeed were analyzed,[4] employing text mining techniques such as topic modeling (Sidorova *et al.*, 2008). The data basis in **Paper IV** is formed from 350 articles related to augmented analytics, which intersects BDA and AI, supplemented by information from service providers active in this area, obtained from Crunchbase.[5] The following subsections explain the corresponding triangulated results of **Paper IV** regarding technical, human, and organizational resources and **Paper II** regarding their operationalization.

3.2.1 Technical Resources

As with BDA, data operations, which provide the infrastructure for integrating and managing data throughout the analytics cycle, are the foundation for AI-related techniques. A major challenge in the context of big data is that they are often scattered across different sources and not structured to accord to a specific data schema as in data warehouses (Oesterreich *et al.*, 2021). This poses a particular problem for the use of supervised AI algorithms as they rely on labeled data to train models (Enholm *et al.*, 2021). Considering that approximately 80% of corporate data are unstructured (Accenture, 2019), the effort required for data scientists to prepare the data, such as collecting, cleansing, and labeling for supervised AI classifiers, is high. For this reason, companies often outsource to a crowdsourcing platform for certain tasks, including data

[2] Research question in **Paper II**, entitled "The Humans Behind Artificial Intelligence – An Operationalisation of AI Competencies" (Anton *et al.*, 2020, p. 2).
[3] Research question in **Paper IV**, entitled "Augmenting the Future: An Exploratory Analysis of the Main Resources, Use Cases, and Implications of Augmented Analytics" (Oesterreich *et al.*, 2021, p. 2).
[4] Platform for the publication or search of job advertisements: www.indeed.com.
[5] Platform that provides information about businesses: www.crunchbase.com.

structuring, such as the annotation of images. Such platforms (e.g., Amazon Mechanical Turk[6]) coordinate a community of collaborators to perform smaller, low-paid tasks. However, the more complex the outsourced tasks are, the less worthwhile crowdsourcing is since besides costing significant time and money, the complexity leads to poor execution and consequently low quality training data (Schuir *et al.*, 2021). **Paper I** helps resolve this problem in the crowdsourcing domain by developing a dedicated augmented reality system that supports capturing objects, labeling data as they are created, and feeding data to a convolutional neural network. Using a design science research approach, the paper thereby addresses the following research question:

(iii) How can the process of capturing and labeling objects be designed and implemented as an augmented reality application for the crowdsourcing community?[7]

Using the developed application, crowdsourced workers can generate labeled data and train convolutional neural network classifiers rather than outsourcing annotation tasks after the unstructured data have already been collected (see the application functionality shown within the system architecture in Figure 5).

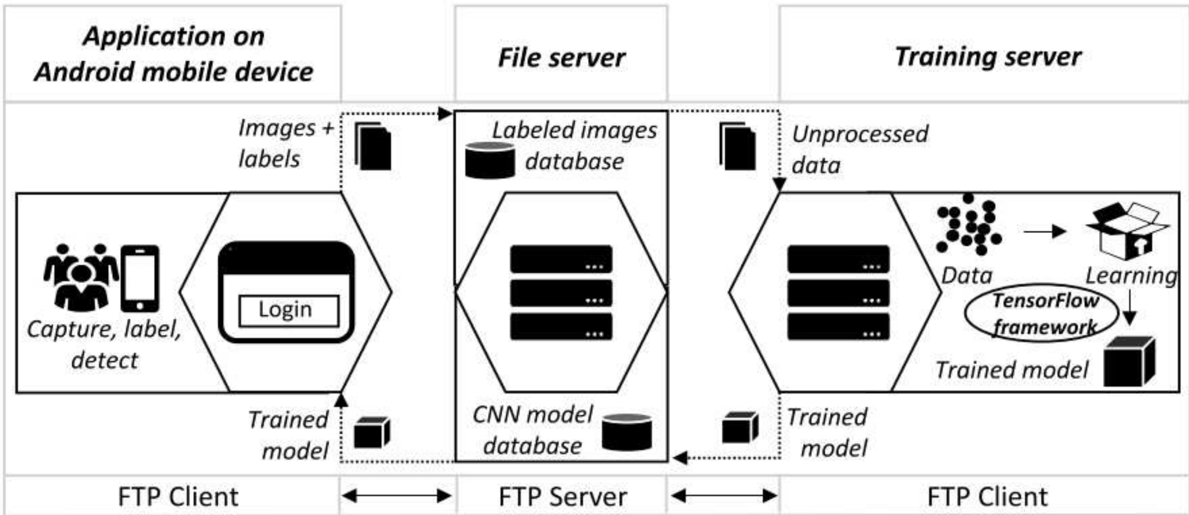


Figure 5 System Architecture for a Device Supporting a Direct Capture, Labeling, and Training Process (Schuir *et al.*, 2021, p. 7)

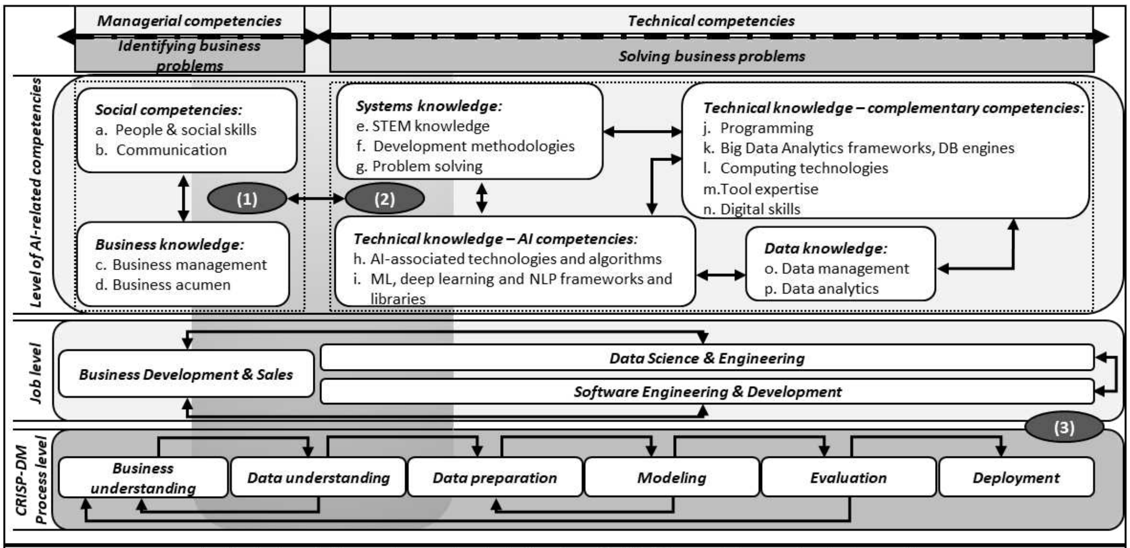
In addition to sourcing models, companies should also focus on data storage and processing strategies that suit big data environments, such as schema-on-read strategies. This schema-on-read approach is useful as data can be stored according to their source schema and are only preprocessed when required, saving effort (Shepherd *et al.*, 2018). Strategies in which data are streamed and processed from different sources based on a schema-on-read baseline usually rely on data lakes and an infrastructure of distributed systems (Munappy *et al.*, 2020). Since processing large datasets, such as during the training of AI-related classifiers, requires high computational power, organizations may deploy cloud solutions to obtain this level of performance (Borges *et al.*, 2021; Enholm *et al.*, 2021). Many cloud providers, such as Amazon and Google,

[6] Amazon Mechanical Turk: www.mturk.com.
[7] Research question in **Paper I**, entitled "Augmenting Humans in the Loop: Towards an Augmented Reality Object Labeling Application for Crowdsourcing Communities" (Schuir *et al.*, 2021, p. 2).

also support the development of AI models by offering AI-dedicated platforms where data processing steps and predefined models can be easily drafted using drag-and-drop functionality, thus enabling even less technically skilled employees to use AI models. Furthermore, the open source world in AI is strongly represented, especially in the area of the programming languages R and Python, which offer a number of frameworks and libraries (e.g., TensorFlow and Scikit-learn) to reduce the programming effort (Anton *et al.*, 2020).

3.2.2 Human Resources

As AI can generally only cover narrow application areas, there is not enough certainty to automate human reasoning in phases such as decision making and identifying business problems and opportunities within the analytics cycle (cf. Figure 3), where responsibility and risk for management are high (Oesterreich *et al.*, 2021). Thus, our results in **Papers I**, **II**, and **IV** show that AI cannot substitute a strong business and technical solution team within organizations that turn data and algorithms into business decisions.



* : Most relevant discussed competencies in literature † : Most demanded competencies in practice
Not labelled (bold and underlined): Most relevant competencies in both practice and literature

a. **Collaboration; building trust; leadership;** people management*; soft skills*; engaging skilled staff (motivatating)*; expectation Management*; emotional intelligence*; teamwork*; networking*; good judgement*; coaching*; tolerating ambiguity*; adaptability*
b. **Communication (oral and written communication);** transparency (explainability of data results)/contextualisation of machine decisions*
c. **Client orientation; decision making;** supervising AI systems*; align business and IT*; guide implementation*; ensure organisational support*; partnership management*; process management*; change management*; risk management*; project management*
d. **Business development - understanding the business, use cases, opportunities and challenges (domain knowledge); interdisciplinary knowledge;** compliance knowledge*; organisational experience*; sales skills†; strategic thinking†
e. **Mathematical & statistical knowledge; computer science;** data and software engineering*; physics†; data informatics*; operations research†; quantitative field†
f. **Agile software development;** design patterns†; data mining and Big Data methodologies (CRISP-DM, 5A, SEMMA)*
g. **Initiative/engagement;** problem solving/design thinking*; creativity*; keen to experiment*; ability to utilise data*; cognitive flexibility*
h. **ML; deep learning; NLP; neural networks;** benefits and limitations*
i. **TensorFlow; Pytorch; Keras; Scikit-learn; Numpy; Caffe;** SciPy*; Theano*; Torch*; MXNet.*
j. **Python; Scala; Java; web development** (CSS, HTML, Javascript, full stack)†; C++*; Node.js†; Go*; R*; MATLAB*
k. **Spark; Hadoop;** Cassandra†; mongoDB†; Hive†; Hbase†; Kafka†; PostgreSQL†; NoSQL†; MySQL†
l. Distributed computing†; edge computing*; cloud computing (Azure; AWS; Google Cloud)†; microservices orchestration (Docker, Kubernetes)†
m. Analytics software*; AI platforms*
n. Digital skills*; digital literacy*; technological skills*
o. **Data management;** data integrity*; data security (intrusion, access)*; data warehouse†; data transformation†
p. Data analytics*; data analysis*; data transformation*; data visualisation*; data interpretation/exploration*; data collection*, data validation*; data synthesis*; data manipulation*; train algorithms*

Figure 6 Explanatory Model Related to Human AI Capabilities (Anton et al., 2020, p. 10)

Figure 6 illustrates the interaction between the business and solution team at the process, job, and human AI competency levels. The process level is formed by the CRISP-DM (Shearer, 2000), a best-practice process model in the analytics realm, which is also the foundation for other models such as the aforementioned analytics cycle (Oesterreich *et al.*, 2021; Prat, 2019). The job level includes a range of roles and functions in the areas of business development and sales, data science and engineering, and software engineering and development. The level of AI-related competencies represents interrelated knowledge and skill categories that relate to the technical and managerial competencies required to operationalize AI.

Borges et al. (2021) emphasize that the value of AI tools only unfolds when their use is aligned with a company's digital strategy. Therefore, companies need business development and sales teams that understand their own business model and market needs to identify opportunities or issues that can be addressed with technology. However, to accomplish this requires them to understand the capabilities of AI tools and the data available and necessary to achieve their business goals, at least on a basic level. Moreover, as the pre-processing and modeling steps become more automated and augmented through AI, business teams can more easily engage in advanced analytics, forming so-called "citizen data scientists" (Oesterreich *et al.*, 2021, p. 9).

Just as the business team needs technical acumen, the technical solution team requires business knowledge to best address the business objectives and requirements through the implementation of AI solutions. Usually, highly technical teams of data scientists, engineers, and software developers work and complement each other in AI software projects throughout the phases of data understanding and preparation, modeling, evaluation, and deployment (Anton *et al.*, 2020). Table 3 lists the key AI-related technical and management competencies distributed among individuals in the business and solution teams based on the results of **Paper II**.

Table 3 Key Technical and Managerial AI Competencies (Anton *et al.*, 2020, p. 12)

Technical Competency (Operationalization)	Managerial Competency (Operationalization)
• Knowledge in AI-associated technologies and algorithms (machine learning, deep learning, and neural networks) • Programming (Python, Scala, Java, and web development) • AI frameworks and libraries (TensorFlow, Pytorch, Keras, Scikit-learn, Numpy, and Caffe) • BDA frameworks (Spark and Hadoop) • STEM knowledge (mathematical and statistical knowledge, as well as computer science) • Development methodologies (agile software development) • Problem solving (initiative and engagement) • Data management	• Business management (client focus and orientation, as well as decision making) • Business acumen (business development and interdisciplinary knowledge) • People and social skills (collaboration, trust, and leadership) • Communication (oral and written communication)

3.2.3 Organizational Resources

The presented technological and managerial resources relate to the individual workforce level. However, organizations must also provide resources and build capabilities at the corporate level (Anton, Oesterreich and Teuteberg, 2021; Enholm *et al.*, 2021; Mikalef and Gupta, 2021; Oesterreich *et al.*, 2021). Our findings show that due to the convergence of big data and AI, a data-driven culture fosters the establishment of innovation and leverages or adopts the data and insights into their existing business model (Anton *et al.*, 2020; Brock and von Wangenheim, 2019). To establish such a fruitful culture, top management is needed to place AI strategically in the organization and to take responsibility for AI decisions. To this end, chief AI officers are increasingly being considered in businesses (Anton *et al.*, 2020; Mohanty and Vyas, 2018). The compatibility between technology and the corporate culture or business model should also be weighed by top management. An innovation only serves a purpose if it can be integrated (Alsheibani *et al.*, 2018). Once AI is established, the organizational change capacity is an important factor in driving adoption (Mikalef and Gupta, 2021) and integrating the technology into the workplace (Makarius *et al.*, 2020).

3.3 Capability Realization Process

The capability realization process includes converting available resources into business value. Capability is defined according to Amit and Schoemaker (1993, p. 35) as "a firm's capacity to deploy resources, usually in combination, using organizational processes, to effect a desired end." The desired end is business value that is influenced by the appropriate use of technology in the context of the sociotechnical system (Soh and Markus, 1995). The effects of the appropriate use of AI can be broadly categorized into automation and augmentation. Automation refers to the substitution of activities previously performed by humans, "while augmentation enhances human intelligence by providing insight that can aid decision making" (Enholm *et al.*, 2021, Section 4.2). Hence, automation enables more efficient processes (e.g., productivity and error reduction) and augmentation provides intelligence that was previously inaccessible due to the amount or type of data (e.g., improved decision quality and organizational agility) to enable informed decision making (Enholm *et al.*, 2021). This study examines these effects in terms of value creation mechanisms and their impact on different value targets.

3.3.1 Value Creation Mechanisms

The effects of activities in the realm of analytics can spill over into business value and are usually operationalized by operational, market, or financial performance measures. IS researchers generally agree on the positive impact of analytics on these performance metrics, but different ideas often exist about how the value creation mechanism functions. These differences are particularly evident in the conceptualization between the direct effect of capabilities on firm performance measures in the area of financial (e.g., return on investment) and market (e.g., market share) indicators and the indirect effect via operational indicators (e.g., business process performance) (Anton, Oesterreich and Teuteberg, 2021). As a possible explanation for the heterogeneous conceptualization, **Paper III** argues that analytics can represent:

> more than a simple information gathering tool that provides some basic performance indicators for operational transparency. Advanced analytics exhibits strategic value by allowing management to use discovery and prediction mechanisms for product innovation or improving customer relationships, in addition to the positive image and signals that a data-driven approach creates in the perception of the organization. (Anton, Oesterreich and Teuteberg, 2021, p. 5)

Therefore, the impact of analytics can affect business value through different pathways. The goal of **Paper III** is to address the heterogeneous conceptualization of IS research and understand the key value creation mechanisms for how capabilities related to the operationalization of BDA and advanced analytics factor into business value. The corresponding research questions are:

(iv) *To what extent do technical, managerial, and organizational BDA capabilities translate into business value in terms of firm performance?*

(v) *To what extent does operational performance play a mediating role in this translation process?*[8]

To answer these questions, meta-analytic structural equation modeling (MASEM) was conducted, combining the strengths of meta-analytic techniques with a variance-based structural path analysis (Cheung, 2015). Addressing the research questions (iv) and (v), the MASEM results depicted in Figure 7 highlight that technical analytics capabilities have a positive relationship with operational performance and indirectly impact financial and market performance. Managerial analytics capabilities, in contrast, directly impact the financial and market dimensions, but their positive effect is also transmitted via the operational dimension. Organizational analytics capabilities have a direct relationship with financial and market metrics.

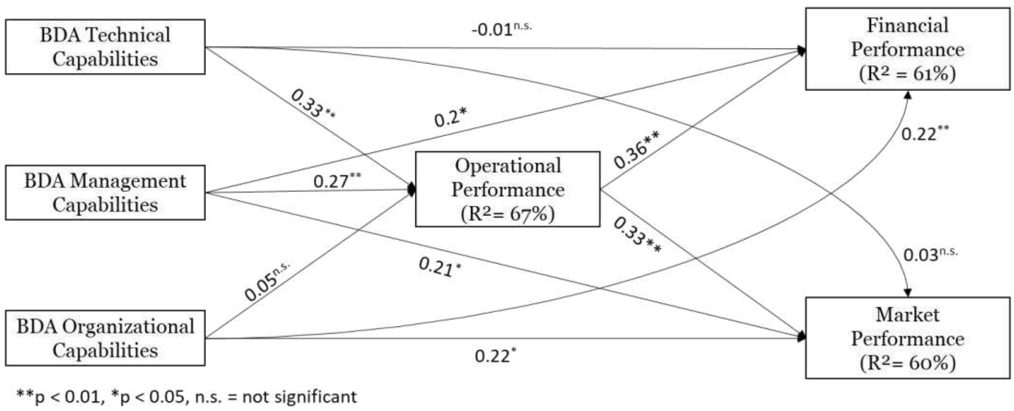


Figure 7 MASEM Results (Anton, Oesterreich and Teuteberg, 2021, p. 9)

The indirect effects via the operational performance are supported by mediation analyses conducted according to Zhao et al. (2010) and Sobel (1982) (see Table 4).

[8] Research questions (iv and v) in **Paper III**, entitled "Understanding the Operational Value of Big Data Analytics Capabilities for Firm Performance: A Meta-Analytic Structural Equation Modeling Approach" (Anton, Oesterreich and Teuteberg, 2021, p. 2).

Table 4 Mediation Analyses Results (Anton, Oesterreich and Teuteberg, 2021, p. 10)

Path	Indirect Effect	95% LBCI: [LB, UB]	a	b	s_a	s_b	Z Value
MC→OP→FP	0.099	[0.028, 0.138]	0.274	0.364	0.096	0.080	2.417*
MC→OP→MP	0.092	[0.025, 0.200]	0.274	0.334	0.096	0.103	2.140*
TC→OP→FP	0.118	[0.052, 0.215]	0.325	0.364	0.073	0.080	3.183**
TC→OP→MP	0.109	[0.037, 0.213]	0.325	0.334	0.073	0.103	2.619**
OC→OP→FP	0.020	[-0.054, 0.083]	0.054	0.364	0.085	0.080	0.634$^{n.s.}$
OC→OP→MP	0.018	[-0.052, 0.082]	0.054	0.334	0.085	0.103	0.628$^{n.s.}$

Comments
LBCI: likelihood-based confidence intervals; LB: lower bound of the 95% likelihood-based CI; UB: upper bound of the 95% likelihood-based CI; a: path of the independent variable to the mediator; b: path of the mediator to the dependent variable; s_a: standard error of a; s_b: standard error of b; $Z = (a * b)/\ (b^2 * s_a^2 + a^2 * s_b^2)^{0.5}$;
significance: ** $p < 0.01$, * $p < 0.05$, not significant (n.s.) for $p > 0.05$;
MC: BDA management capabilities; TC: BDA technical capabilities; OC: BDA organizational capabilities; OP: operational performance; FP: financial performance; MP: market performance.

3.3.2 Value Targets and Impact of Artificial Intelligence

Beyond considering how value transmission occurs in the capability building process, this cumulative dissertation also examines how AI's impact is manifested in specific value targets. In their BDA business value framework, Grover et al. (2018) list various possible value targets, such as product and service innovations at the strategic level or business process improvements at the operational level. However, Krishnamoorthi and Matthew (2018, p. 644) emphasize that the "value creation process is different for various technologies." It is therefore necessary to understand the nuances between different technologies or concepts. Thus, this dissertation investigates how the automation and augmentation effects of AI use manifest in specific value targets by studying its impact on different sectors.

Paper V investigates AI-induced business model innovations in the electric power industry by classifying the services and offerings of start-ups enabled by AI augmentation and automation. In doing so, a business model taxonomy related to the AI frontier was developed and commonly manifesting business models were clustered into archetypes to obtain an overview of this competitive environment. The associated research questions are:

(vi) *What are the dimensions and characteristics of business models of AI start-ups in the electric power industry that can be integrated to develop a business model taxonomy?*

(vii) *Which business model archetypes can be identified based on the distinct patterns of AI start-ups in the electric power industry?*[9]

After analyzing 40 studies and 71 start-ups as well as interviewing 12 experts from the energy industry, the results formed the taxonomy depicted in Figure 8. The taxonomy reveals that AI-driven products and services are widely deployed among energy utilities and service providers. In particular, these companies are taking advantage of AI capabilities to analyze various types

[9] Research questions (vi and vii) in **Paper V**, entitled "A Business Model Taxonomy for Start-Ups in the Electric Power Industry — The Electrifying Effect of Artificial Intelligence on Business Model Innovation" (Anton, Oesterreich, Schuir, *et al.*, 2021, p. 3).

of data related to electricity consumption, market, financial, and business information to create cost savings or new revenue sources across the energy supply chain.

Dimensions		***Characteristics***					
Value proposition	*Offering*	Software	Software and services	Software, services and physical products			
	Key activity	Decision and strategy	Energy storage	Maintenance and safety	Energy consumption efficiency	Investment and trade	Co-creation
	Monetary value	Cost saving	Cost saving and additional revenue	Additional revenue	Intangible value		
	Customer segment	B2B	B2C	B2B and B2C			
Value architecture	*AI technology*	Data processing (processing data related to power consumption, market, finances, other business information)	Computer vision (processing image or video data)	Robotics	Natural language processing (processing text-based or audio files)		
Value network	*Supply chain segment*	Energy generation-/supply-oriented	Consumption-oriented	Distribution-oriented	Overarching (not restricted to a segment)		
	Energy system	Decentral	Central	Independent			
Value finance	*Revenue stream*	Product- and license-based	Subscription	Performance-based and case-by-case based			

Figure 8 Business Model Taxonomy in Relation to the AI Frontier in the Electric Power Industry (Anton, Oesterreich, Schuir, *et al.*, 2021, p. 14)

The archetypes summarized in Table 5 provide a more detailed picture of the application areas in which business model innovation is occurring and in which new fields are emerging through the innovating capacity of AI. These archetypes empirically confirm, in a specific sector, the previously conjectured impact of AI on decision support, customer and employee engagement, automation, and product and service innovation (Borges *et al.*, 2021; Enholm *et al.*, 2021). **Paper IV** extends these findings by highlighting the impact of augmented analytics on various activities within other sectors and also delves into its societal value by addressing the following research question:

(viii) *What are the main fields of application and use cases of augmented analytics, and what implications does the emergence of augmented analytics entail for business and society?*[10]

[10] Research question in **Paper IV**, entitled "Augmenting the Future: An Exploratory Analysis of the Main Resources, Use Cases, and Implications of Augmented Analytics" (Oesterreich *et al.*, 2021, p. 2).

The mixed-methods approach shows the effects of augmented analytics within the banks, financial services, and insurance (BFSI); transportation and logistics; and healthcare sectors. As in the energy sector, AI-powered analytics enable more accurate forecasting and continuous auditing and monitoring of processes to improve decision quality, reduce human error, and automate supply chain tasks in transportation and logistics or fraud detection in the financial sector. However, AI has a societal dimension, particularly in relation to augmented personalized healthcare, because the continuous monitoring and analysis of data can provide personalized and real-time recommendations for people's health. Additionally, social bots care for individuals who are lonely or sick. This social dimension of AI can both relieve the healthcare sector and lead to a healthier society.

In addition, **Paper IV** highlights the inner effect of AI within the analytics cycle. AI's effect on the operational dimension can be divided into an inner effect, which automates or supports the processes and activities in the analytics cycle, and an outer effect, which results from the business process improvements derived from the analytics outcomes or the automation of tasks beyond the analytics cycle.

Table 5 Archetypes in the Electric Power Industry (Anton, Oesterreich, Schuir, *et al.*, 2021, pp. 20–21)

Archetype	Description
Customer cost control and management	This archetype focuses on white label services for utilities. The start-ups enable companies to implement data-driven, customized customer management; customers are primarily companies that provide services to their end consumers. Cross-selling complementary services are often part of the start-ups' strategy.
Data analysis	This archetype includes start-ups with business models that encompass data analysis and management in their service portfolio to assist their customers in decision making based on data-driven support.
Electromobility and battery management	Business models of this archetype focus on electromobility and the battery sector and include areas such as research and development, battery system management, and charging infrastructure for electric vehicles.
Maintenance and safety	Start-ups of this archetype are specialized to use robots, drones, satellite imagery, or sensor data to monitor and maintain infrastructure in the electric power industry (e.g., power lines, wind turbines, and photovoltaic plants).
Investment and trade	These business models aim at maximizing profits and return on investment for energy producers, for example through investment consulting, market forecasts, production or storage adjustments according to market conditions by using AI data analysis methods.
Market transparency	Start-ups of this archetype reduce information asymmetries and uncertainties in the market for their customers, thus improving market efficiency. Intelligent trading, multisided platforms, and demand response management are often used for this purpose.
Smart building	Smart building business models focus on optimized energy consumption in buildings and households. Both private households and businesses are addressed with offers that include software and physical solutions.
Independent energy supply	Start-ups of this archetype enable their customers to be largely independent of conventional energy suppliers by offering integrated storage and photovoltaic systems as well as intelligent regional energy trading.

3.4 Value Manifestation–Artificial Intelligence Adoption

To support the conversion of AI capabilities into business impact, AI adoption must be managed; otherwise ,the "dark side" of AI can inhibit the effects (Berente *et al.*, 2021; Rana *et al.*, 2021). Repeated reports claim that due to insufficiently diversified training data, biases such as sexism or racism appear in the algorithmic results, therefore rendering them unsuitable and dangerous for decision making. In medicine, such flawed data can even lead to health consequences (Zou and Schiebinger, 2018). AI's ability to analyze data such as videos and images to perform real-time security analyses also raises ethical concerns, such as the dichotomy between security and privacy (Anton, Kus, *et al.*, 2021; Berente *et al.*, 2021). Concerns about this flipside of AI are so widespread that the European Commission is devising ethical guidelines for trustworthy AI and issuing cautions:

> While offering great opportunities, AI systems also give rise to certain risks that must be handled appropriately and proportionately. We now have an important window of opportunity to shape their development. We want to ensure that we can trust the socio- technical environments in which they are embedded. (European Commission, 2019, p. 4)

As the European Commission points out, establishing trustworthy AI artifacts is an important building block to enable the acceptance and adoption of such technology. Enholm et al. (2021, Section 5.5) confirm that "organizations adopting AI must be aware of the role of trust, how to build trust, and in turn, how trust influences their reputation and interaction with external stakeholders." However, in IS research, empirical research on the effect of trust on AI artifacts is sparse and often contains heterogeneous conceptualizations and results (Anton, Oesterreich, Fitte, *et al.*, 2022; Anton, Oesterreich, Schuir, *et al.*, 2022). **Paper VII** builds on this issue by seeking to understand, in the context of conversational AI, whether there is trust in the technology and to what extent this trust influences other factors related to technology acceptance. The study goal is to derive appropriate implications for the development of such tools. The corresponding research question is:

(ix) *What is the role and influence of trust on the intention to adopt conversational agents within the nomological network of the technology acceptance model (TAM)?*[11]

For this purpose, a MASEM based on 45 studies comprising 155 correlations and 13,786 observations was conducted, which yielded the results shown in Figure 9 and the corresponding path and mediation analysis in Table 6.

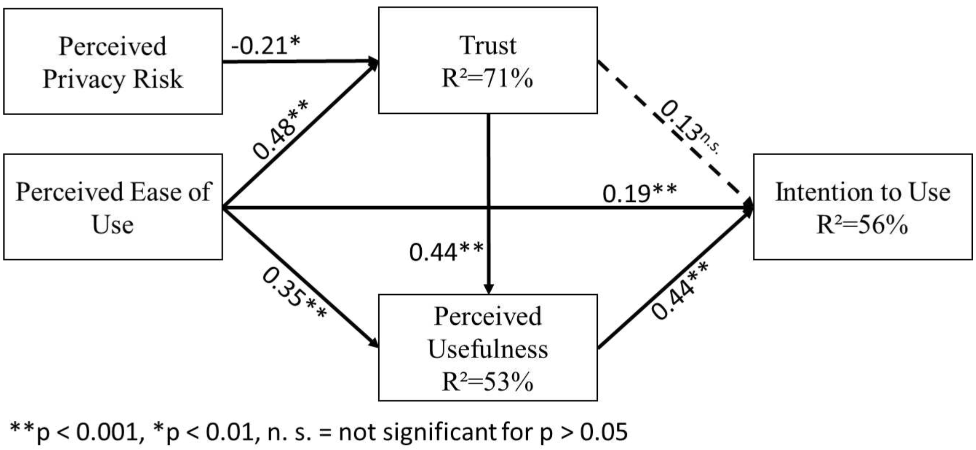


Figure 9 MASEM Results of **Paper VII** (Anton, Oesterreich, Schuir, *et al.*, 2022, p. 5875)

[11] Research question in **Paper VII**, entitled "Painting A Holistic Picture of Trust in and Adoption of Conversational Agents: A Meta-Analytic Structural Equation Modeling Approach" (Anton, Oesterreich, Schuir, *et al.*, 2022, p. 5872).

The meta-analytic results show that trust is no direct antecedent of intention to use; instead, it strongly affects perceived usefulness, which mediates the effect of trust on intention to use. Furthermore, trust is related to perceived ease of use in that trust has a complementary mediator function between perceived ease of use and perceived usefulness. Moreover, privacy risks can negatively influence trust in such AI technologies. Thus, **Paper VII** shows that while trust does not directly affect adoption, it is an important component in the nomological network that leads to the adoption of conversational AI.

Table 6 Path and Mediation Analysis (Anton, Oesterreich, Schuir, *et al.*, 2022, p. 5875)

Path	Direct Effect	Z Value	Indirect Effect	95% LBCI: [LB, UB]	Total Effect
PU→IU	0.44	4.55	-	-	0.44
PE→IU	0.19	3.17	0.15	[0.08, 0.23]	0.34
PE→PU	0.35	8.07	0.21	[0.16, 0.28]	0.56
PE→TR	0.48	12.92	-	-	0.48
TR→IU	n.s.	0.75	0.19	[0.11, 0.31]	0.19
TR→PU	0.44	8.70	-	-	0.44
PR→TR	-0.21	-2.36	-	-	-0.21

Comments
LBCI: likelihood-based confidence intervals; LB: lower bound of the 95% likelihood-based CI; UB: upper bound of the 95% likelihood-based CI; total effect = direct effect + indirect effect; n.s. = not significant;
PR: perceived privacy risk; PE: perceived ease of use; TR: trust; PU: perceived usefulness; IU: intention to use.

In addition to trust, according to Berente et al. (2021), the ethical dimension requires more consideration from management. As in the area of trust, however, hardly any empirical approaches consider the extent to which AI technology is perceived as ethically questionable and how such views can be addressed (Anton, Kus, *et al.*, 2021; Seppälä *et al.*, 2021). Therefore, **Paper VI** empirically investigates this matter and examines the ethical aspects with regard to the dichotomy between privacy and security. In particular, the paper focuses on AI-based surveillance analytics. With this technology, video data can be immediately analyzed using deep learning methods and compared against, for example, biometric data. This technology is gaining increasing relevance, especially since the coronavirus disease 2019 (COVID-19) outbreak, as it can enable patients to be monitored or locate them in public places. In addition, the technology can also be used for everyday surveillance, for example to monitor people crossing an intersection on a red light or pickpockets in public places. Although these examples protect the public, such surveillance intrudes on the privacy of individuals. A sample of 201 individuals was surveyed about these three scenarios (i.e., COVID-19, jaywalking, and pickpocketing) to determine whether the perceived usefulness justifies the invasion of privacy from an ethical perspective. Accordingly, **Paper VI** poses the following corresponding research question:

(x) How does the perceived usefulness of AI-based surveillance technologies affect the moral intent to accept the public application of these technologies?[12]

For this research, a fuzzy set qualitative comparative analysis (fsQCA) was applied to investigate the configurational effect of several independent variables on the moral intent to accept

[12] Research question in **Paper VI**, entitled "Is Ethics Really Such a Big Deal? The Influence of Perceived Usefulness of AI-Based Surveillance Technology on Ethical Decision-Making in Scenarios of Public Surveillance"(Anton, Kus, *et al.*, 2021, p. 2122).

AI-based surveillance. Table 7 lists the results for each scenario. The notation presented in the table was adopted from Ragin and Fiss (2008), where "●" stands for sufficient conditions that imply the occurrence of an outcome. The symbol "⊗" represents the absence of a condition that contributes to the outcome. Blank fields represent a condition that does not contribute to the outcome under study. The size of the symbols indicates the centrality of the condition for explaining the outcome. The results show that the perceived usefulness of the surveillance is a decisive factor in how far a given scenario is interpreted as ethically questionable and thus enables acceptance of the technology. Therefore, the perspective of technology acceptance is directly linked to the ethical decision making that informs the use of surveillance analytics and related organizational change management and marketing measures.

Table 7 fsQCA Results of **Paper VI** (Anton, Kus, *et al.*, 2021, p. 2126)

		Configurations			
		Moral Intent to Accept AI–Based Surveillance		**~Moral Intent to Accept AI–Based Srveillance**	
#	**Antecedents**	**1**	**2**	**3**	**4**
Scenario-1: Jaywalking	Moral equity	●		⊗	
	Perceived importance of the ethical issue	●			⊗
	Perceived usefulness	●		⊗	⊗
	Gender*				⊗
Scenario-2: COVID-19	Moral equity		●	⊗	
	Perceived importance of the ethical issue	●	●		
	Perceived usefulness	●	●	⊗	
	Gender*	⊗			
Scenario-3: Pickpocketing	Moral equity	●		⊗	
	Perceived importance of the ethical issue	⊗			
	Perceived usefulness	●		⊗	
	Gender*	●		●	
Consistency	Scenario-1 Scenario-2 Scenario-3	0.890 0.905 0.890	- 0.892 -	0.959 0.905 0.941	0.919 - -
Raw coverage	Scenario-1 Scenario-2 Scenario-3	0.671 0.334 0.208	- 0.619 -	0.643 0.705 0.354	0.290 - -
Unique coverage	Scenario-1 Scenario-2 Scenario-3	0.671 0.082 0.208	- 0.366 -	0.396 0.705 0.354	0.042 - -
Overall solution consistency	Scenario-1 Scenario-2 Scenario-3	0.890 0.895 0.890		0.945 0.905 0.941	
Overall solution coverage	Scenario-1 Scenario-2 Scenario-3	0.671 0.701 0.208		0.686 0.705 0.354	

Comments
* = presence/negation reflects "male";
● = presence of an antecedent; ⊗ = negation of an antecedent; large circle = core element; small circle = peripheral element; blank space = subordinate antecedent.

3.5 Methodological Foundations for QCA Research

Paper VIII (Anton, Oesterreich and Teuteberg, 2022), unlike the other papers, does not address capability building and realization in context of AI-driven analytics, but focuses on the conduct of QCA in the IS literature and provides guidance for scholars who wish to apply QCA as a research method. As such a methodologically oriented paper, it provides guidance for **Paper VI,** which employs QCA (specifically the associated fsQCA technique).

QCA is still a fairly new method in IS research and was first referenced in the IS literature in 2004 (Fichman, 2004). Since then, the methodology has been gaining momentum and is found as the main or complementary approach in leading IS conferences and journals (cf. Figure 10).

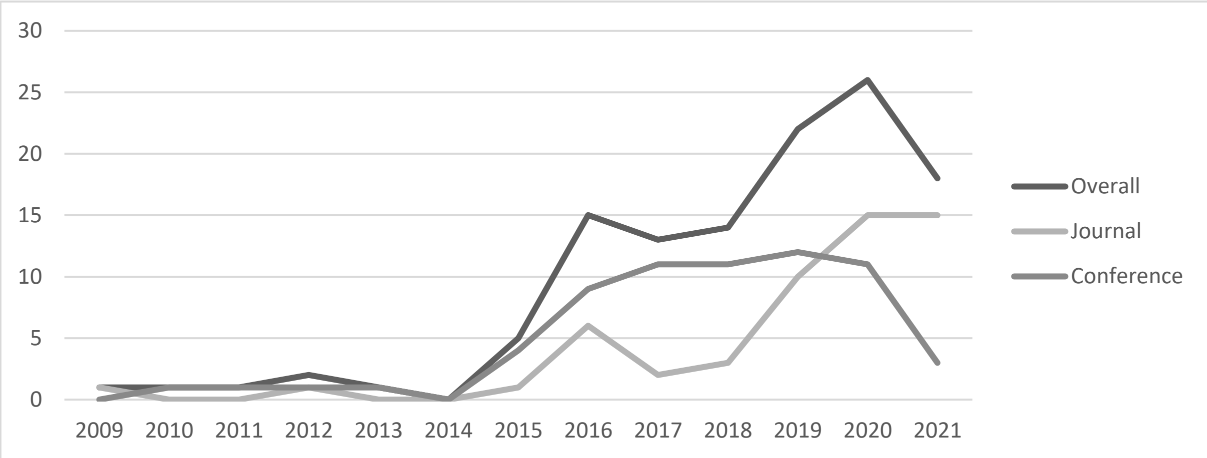


Figure 10 Number of Conducted QCA Studies in IS Research (based on **Paper VIII** results)

Originally, the methodology was introduced by Ragin (1987) in the context of political science to combine the strengths of qualitative (case-based) and quantitative (variable-based) methods in a configurational approach. QCA is not just a tool for data analysis, but must be embedded in the theoretical foundations as a configurational approach (Schneider and Wagemann, 2012). Due to the novelty of the method and the comprehensive nature of the approach, there are major pitfalls that often lead to results with atheoretical configurations (Park, Fiss, *et al.*, 2020). **Paper VIII** aims to highlight flawed QCA use in the IS literature and provide recommendations for improvement for future QCA research. To this end, the following research questions were posed:

(xi) *What are the main patterns of QCA practices in IS research and how have they evolved over time?*

(xii) *To what extent do QCA studies in the IS field show deviations from the recommended best practices in the extant literature and what are issues for further improvement?*[13]

To answer these questions, a systematic literature review was conducted in which 119 QCA papers from 12 years of IS research were identified and analyzed in terms of their methodological conduct. The results reveal weaknesses in the QCA conduct, particularly with respect to

[13] Research questions (xi and xii) in **Paper VIII**, entitled "The Property of Being Causal – The Conduct of Qualitative Comparative Analysis in Information Systems Research".

the theoretical grounding, lack of robustness testing, and insufficient transparency in the explicating methodological steps and in the presentation of results. Based on these findings, 19 recommendations for the IS literature were derived drawing on best practices from seminal work (e.g., Rihoux and Ragin, 2009; Schneider and Wagemann, 2012). These recommendations were considered in **Paper VI** to ensure the rigor of the methodological procedure.

4 Discussion

Enabling data-driven decision making is a central theme of many modern digital strategies (Curuksu, 2018). In this context, expectations are often placed on AI-driven analytics to exploit the unutilized information potential of big data (Rana *et al.*, 2021). However, companies regularly fall short of their expectations when AI is anticipated to function as a "plug-and-play technology with immediate benefits" (Fountaine *et al.*, 2019, p. 4). Instead, AI demands a holistic organizational approach that aligns AI adoption and capability building to deliver business value (Enholm *et al.*, 2021; Fountaine *et al.*, 2019; Mikalef and Gupta, 2021). This dissertation addresses the frequently absent knowledge of how to effectively operationalize AI-driven analytics in terms of building capabilities and creating business value. The explanatory model in Figure 11 summarizes the results and illustrates the relationship among the results of the eight individual research contributions (**Papers I–VIII**).

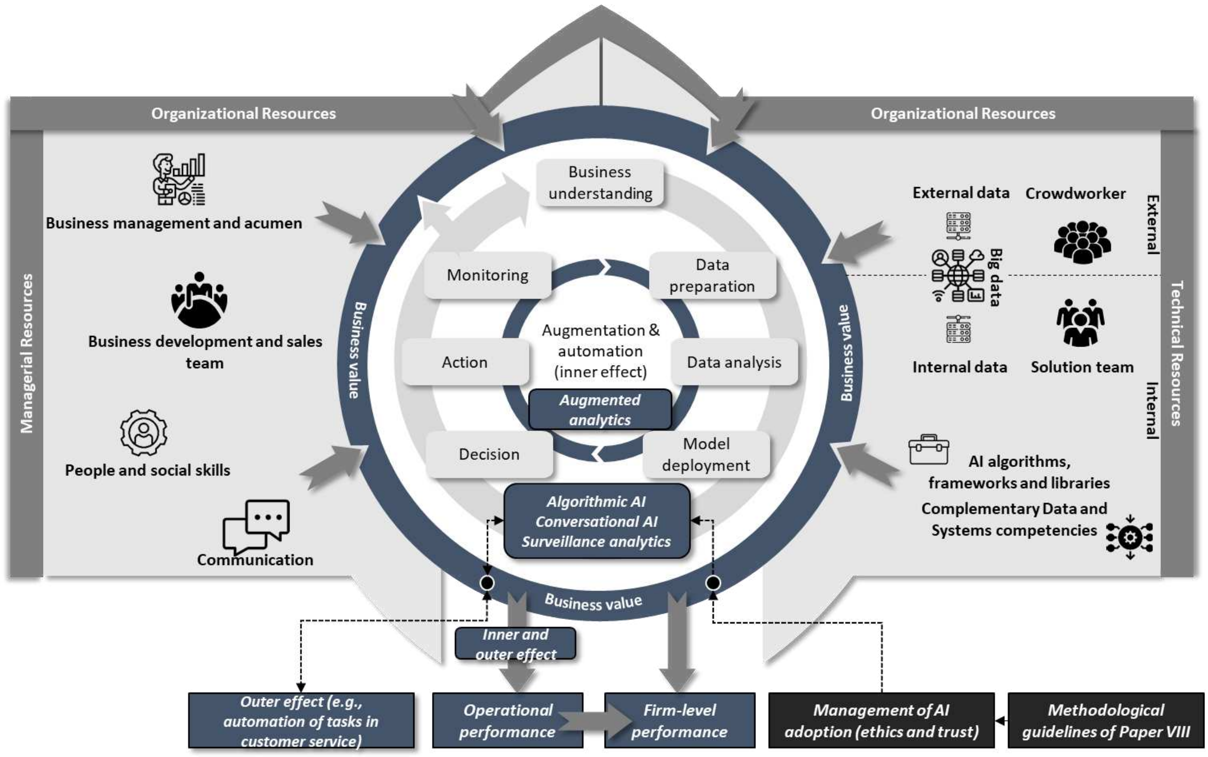


Figure 11 Explanatory Model

Thereby, this dissertation builds on Grover et al.'s (2018) BDA business value model and examines the specifics of AI-driven analytics along the processes of capability building, capability realization, and value manifestation. The exploratory model not only highlights the particularities of AI-driven analytics, but also embeds the aforementioned three processes into the analytics cycle and operationalizes analytics from implementation to business value. While **Papers I**, **II**, and **IV** contribute to the operationalization of AI resources, **Papers III**, **IV**, and **V** engage in the capability realization process, namely how technical, organizational, and managerial AI capabilities affect organizational performance and translate into business impact in different value targets. **Papers VI** and **VII** complement implications of managing AI adoption by addressing ethical and trust-related issues that influence the conversion of AI measures into business value. **Paper VIII** contains methodological guidelines underlying the QCA paper (**Paper VI**). Sections 4.1 and 4.2 discuss the overarching implications for theory and practice, and Section 4.3 outlines the related limitations.

4.1 Theoretical Implications

This dissertation provides several theoretical implications by addressing the overarching research objective, which is to enhance understanding of the process of building and realizing capabilities related to the use of AI-based analytics. While this area of research is under-studied (Borges *et al.*, 2021; Enholm *et al.*, 2021; Makarius *et al.*, 2020; Mikalef and Gupta, 2021), it is important as Chui et al. (2018) emphasize that the scalability and value of AI in organizations do not depend on the techniques themselves but rather rely on the organizational capabilities to deploy the algorithms in the business context.

To address the overarching research question, the RBV provides a theoretical lens for examining how IS and IT resources affect firm value, but this theory is often insufficient to explain the utilization mechanisms with other resources that are reflected in performance measures (Wade and Hulland, 2004). Thus, drawing on RBV and IT business value research (Grover *et al.*, 2018; Melville *et al.*, 2004; Schryen, 2013), this dissertation operationalizes technical AI resources, identifies mechanisms of their effective use in conjunction with other managerial and organizational resources and their impact on business value, and integrates them into an explanatory model (cf. Figure 11). This approach provides a holistic, process-based perspective that considers the interdependency with sociotechnical aspects and complements related work that focuses more narrowly on AI capabilities (Mikalef and Gupta, 2021) and sociotechnical considerations related to AI adoption (Makarius *et al.*, 2020). In addition, by focusing on AI-driven analytics, the results augment Grover et al.'s (2018) BDA business value framework by highlighting the particularities of AI use.

Papers II and **IV** operationalize which assets and capabilities fall within the realm of AI and how they can be leveraged along the processes of frameworks, such as the analytics cycle (Prat, 2019) or the CRISP-DM (Shearer, 2000). Although previous work on building AI capabilities has neglected this connection to the generic processes of analytics (Enholm *et al.*, 2021; Makarius *et al.*, 2020; Mikalef and Gupta, 2021), it is important given that AI is predominantly deployed in use cases related to analytics (Chui *et al.*, 2018). Furthermore, **Paper I** extend previous considerations in this context by considering how capabilities from external crowdsourcing communities can be integrated into these analytics processes by providing design knowledge for the development of an artifact dedicated to data preprocessing. Recognizing that big data projects often fail due to inadequate project management and process methodology in data science (Saltz *et al.*, 2018), this dissertation provides a systematic process approach based on the analytics cycle and incorporates a team perspective that includes the technical solution and business team and joins the required competencies along the process steps.

Furthermore, this work addresses the realization of capabilities, meaning the leveraging of resources to generate value from big data by employing techniques related to AI-driven analytics.

Paper III contributes to value creation mechanisms by examining how analytical capabilities translate into business value. According to Melville et al. (2004), IT business value manifests itself in efficiency, which is the improvement of business processes in terms of productivity and cost reduction, as well as in effectiveness, which addresses the market and financial metrics for competitive advantage. Previous research on business value in the realm of analytics has been heterogeneous in its approach in that different avenues have been explored and validated by showing either the direct impact of analytics on effectiveness at the firm level (Aydiner *et al.*, 2019; Behl, 2020; Ferraris *et al.*, 2019) or the intermediate impact on efficiency via operational performance at the process level (Asadi Someh and Shanks, 2015; Ashrafi and Zare Ravasan, 2018; Torres *et al.*, 2018). The conceptualization of mediating effects via operational performance is based on process-oriented IT business value models such as that of Melville et al. (2004), in which the effects of resources and capabilities render business processes more productive and cost efficient, which improvement is then reflected in the firm-level performance. The use of advanced analytics increases the efficiency of business processes through automation and augmentation, provided that the technical capabilities and management direction are available within an organization. However, the findings in **Paper III** show that managerial and organizational capabilities also directly impact the firm-level performance as insights can be used to innovate products and services and improve the quality of customer and vendor relationships, as well as the image and signals to stakeholders that emanate from the use of advanced analytics and a data-driven culture (Anton, Oesterreich and Teuteberg, 2021). Therefore, the meta-analytic approach in **Paper III** is valuable for future research as it provides a clear understanding of the value creation mechanisms that can be used for the theory building of empirical research models or theoretical grounding.

In addition to the mechanisms of value transmission from capabilities to business value, **Papers IV** and **V** also examine how AI exerts its impact on specific value targets. Chui et al. (2018) have shown that the capabilities and potential of AI-powered analytics depend on the industry and specifics of the sector. AI is particularly potent in customer-facing industries and areas where operational excellence is at stake, such as supply chains, because the added value resides in the improvement of existing analytics use cases in organizations (Chui *et al.*, 2018). The results in **Paper V** within the electric power industry confirm these findings as the AI frontier improves business processes in various supply chain segments of the electric power industry. However, the results provide evidence that these improvements can lead to new services and product innovations that change the market in the long term. For example, AI-enabled smart energy services and improved energy efficiency can lead to better environmental outcomes while creating new products, services, and enhancements for customers and the market, thus fostering economic growth. In addition to the economic implications, the results also show the social and ecological potential of AI for shaping the future in a sustainable way (Anton, Oesterreich, Schuir, *et al.*, 2021; Vinuesa *et al.*, 2020). **Paper IV** contributes similar implications related to the BFSI, transportation and logistics, and healthcare sectors, in which innovation emerges from improving the quality of decision making and business processes (Oesterreich *et al.*, 2021). While the literature on the business value of analytics considers these aforementioned value targets (Grover *et al.*, 2018), the impact of AI on the analytics processes is often neglected. Therefore, **Paper IV** complements the previously considered value targets by considering AI-enabled automation and augmentation of the analytics cycle processes. Existing research on augmented analytics (Prat, 2019), has neglected the differentiation of value targets in a holistic framework. Therefore, this work complements previous research by differentiating between an inner and an outer efficiency effect, where the inner effect emanates from the deployment of augmented analytics and the outer effect results from operational transparency through information dissemination and the automation of activities such as customer service through conversational AI.

The conversion of AI resources and capabilities to business value can be influenced by adopting enablers and inhibitors (Berente *et al.*, 2021; Enholm *et al.*, 2021; Mikalef and Gupta, 2021). Due to the aforementioned complexity and hybrid nature of AI technology, Berente et al. (2021) foresee that future IS literature will have to primarily deal with the management of AI issues, such as establishing trustworthy IT artifacts and solving issues related to moral and ethical aspects. This dissertation agrees with that assessment and provides an enhanced understanding of and recommendations for managing AI to strengthen adoption while addressing the drawbacks of AI (Rana *et al.*, 2021), thus supporting the conversion of AI capabilities to business impact. **Paper VI** contributes an empirical ethical perspective on the use of AI in surveillance scenarios to otherwise primarily conceptual approaches (Seppälä *et al.*, 2021). Thereby, it expands the literature on ethical decision making (Haines and Haines, 2007; Robin *et al.*, 1996) by introducing constructs from IT adoption research (Davis, 1989) within a single research design and also provides a new approach to addressing ethical issues in the IS domain. **Paper VII** confronts the challenge of trust towards AI in the context of conversational agents. In doing so, the paper examines meta-analytically the relationship between trust and other constructs of the TAM to provide a more consistent view of the previously mostly heterogeneous findings on the effect of trust on conversational AI (e.g., Etemad-Sajadi, 2014; Kasilingam and Soundararaj, 2020; Moussawi *et al.*, 2021; Pitardi and Marriott, 2021). The results show that in the context of conversational AI, trust is not a direct determinant of adoption intention but rather an enabler within the nomological network of the TAM. However, more research is needed in different contexts and domains to study whether the direct effect depends on the level of risk associated with the use of conversational AI (Anton, Oesterreich, Schuir, *et al.*, 2022). For example, Pitard and Marriot (2021) do not consider trust towards conversational agents to be essential in scenarios such as smart home device control, yet the use of such bots for health indicator analytics can be more trust sensitive (Anton, Oesterreich, Fitte, *et al.*, 2022).

Finally, this cumulative dissertation includes a broad methodological spectrum that incorporates relatively new and promising approaches to deductive (MASEM) and abductive (QCA) research inquiries in the IS field (Jak, 2015; Liu *et al.*, 2017). Future research can benefit from the methodological rigor and detailed procedural descriptions of the MASEM in **Papers III** and **VII** and QCA in **Papers VI** and **VIII** and apply them to other contexts. In particular, **Paper VIII**, as a review paper on the conduct of QCA, identifies ways to improve methodological patterns in IS research and highlights worthwhile research areas for the application of QCA. This not only helps in guiding individual research projects, but can also help in improving the rigor of QCA research in IS and other research areas.

4.2 Implications for Practice

Due to the organizational focus of this work, this dissertation has a high practical relevance with implications for individual stakeholders.

The explanatory model in Figure 11 operationalizes that while organizational capabilities form the basis for AI initiatives, for example through a data-driven culture, technical capabilities are in greater demand in the early stages of data preparation, model development, and deployment, while insights from model outputs must be effectively used by management, which requires business acumen. This model can help management first understand the complexity of AI implementation involving the orchestration of resources and subsequently derive a competency development program. In terms of capability building to effectively implement AI capabilities in an organization, **Papers II** and **IV** highlight the required technological, human and organizational resources, including assets and capabilities. This overview provides insights to assess the status quo of existing resources, based on which interdisciplinary training, job matching, and complementary management can be introduced. Alternatively, the results can be used to inform job postings, staffing decisions, and AI team building. In addition, **Paper I** provides design knowledge that can be exploited by companies when planning to involve crowdsourcing workers in the data preparation process. The results have shown how crowdsourcing workers can efficiently and effectively gather labeled training data (images) and directly feed them into the training process of convolutional neural networks.

In terms of capability realization, the results from **Paper III** help management better understand the mechanisms of value creation and thus more effectively formulate goals and allocate resources with respect to specific initiatives. In particular, the results emphasize that management should not seek financial and market-based metrics directly but rather consider the operational efficiencies that AI can deliver through automation and augmentation. **Papers IV** and **V** show the domains and use cases in which AI effects are profitable for companies. The papers demonstrate how AI can inevitably lead to the innovation of new products and services and thus business model innovation. The insights help identify opportunities for companies; classify their business models in an existing taxonomy, as in the case of **Paper V**; and use it to evaluate the market.

Regarding the management of AI adoption, **Papers VI** and **VII** examine ethical and trust-related issues. Although these empirical studies were conducted from the perspective of the user or monitored individual, there are still implications for organizations. The correlations from **Paper VI** between the perceived importance of an ethical issue and the perceived usefulness of the surveillance scenario can be used to guide AI surveillance analytics measures and adoption with respect to information campaigns and change management measures. Furthermore, regulatory institutions can use the results to determine which situations are considered ethically questionable in Western Hemisphere cultures and accordingly weigh whether certain surveillance scenarios are justifiable. The results thus provide evidence in a level of detail previously lacking in ethical conceptual guidelines (Seppälä *et al.*, 2021) of what is considered ethical and how conclusions regarding ethicality in decision making are reached. **Paper VII** contributes to the understanding of the design aspects of conversational AI that improve the trustworthiness of technologies such as conversational agents. Nevertheless, the paper demonstrates that in this context, companies should not necessarily focus on strengthening trust but rather on the performance of the tool, which factor is a proximate determinant of adoption.

4.3 Limitations and Future Research

The eight papers included in this cumulative dissertation have already undergone a multi-stage double-blind review process and met the high-quality standards of reviewers and editors of leading IS conferences and journals in terms of their theoretical or practical relevance and methodological rigor. **Paper III** was even awarded with the Best Paper in Track Award and nominated for the Overall Best Paper Award at the *International Conference on Information Systems 2021*. Nevertheless, this cumulative dissertation and the incorporated individual papers have limitations, in light of which the results must be evaluated.

The results of the overarching cumulative dissertation must be interpreted in consideration of three points. First, based on numerous different algorithms and technologies, inferences for the AI frontier of analytics were made in this dissertation, which threatens the construct validity. However, in this dissertation, the inference goals are elucidated and theoretically supported to effectively “mix apples and oranges, as one necessarily would do in studying fruits” (Smith *et al.*, 1980, p. 47). Nevertheless, the results of this work cannot be generalized to other technologies associated with AI, such as robotics (Bawack *et al.*, 2019). Future work should conduct its own research for capability building and realization for these technologies and disclose the differences to this work. Furthermore, the AI frontier is constantly expanding with emerging use cases and technological advances that must be addressed through future research (Berente *et al.*, 2021). Second, the complexity of AI makes it possible to explore diverse aspects and nuances. Therefore, this work does not claim to be exhaustive. Future work may, for example, more intensively examine adoption issues arising from the black-box problem of deep neural networks inhibiting explainable AI or regulatory issues that limit data processing or deployment in highly regulated industries. Other factors also need to be investigated in the area of capability building, such as the influence of top management or compatibility with the business model (Enholm *et al.*, 2021). Since most of the work to date has been of a conceptual nature, empirical work in this area would be valuable. Third, the empirical work in **Papers VI** and **VII** is primarily concerned with the user perspective on the technologies studied. While implications for the organizational framework of this dissertation can be drawn from these papers as well, future research should validate the presented results in an organizational context.

At the level of individual contributions, limitations associated with the applied methodologies must be considered. Systematic literature reviews formed the foundation of all the included papers. Although the literature reviews were based on the best practices of vom Brocke et al. (vom Brocke *et al.*, 2009), only a limited number of databases were searched with queries that may not have uncovered all the relevant work. Notwithstanding, the search strategy was based on databases and search terms resulting from the respective research question to address this limitation in the best possible way. There is also the potential for subjective bias in the selection of relevant literature. This bias could also have occurred in the coding of qualitative data (**Papers II**–**V** and **VII**–**VIII**). To counteract this, an interrater agreement of at least two coders was used to validate the literature selection and coding (Landis and Koch, 1977).

Furthermore, the results of the quantitative content analyses (**Papers II** and **IV**) should be interpreted with the knowledge that the text mining methods used, such as topic modeling, are reduction methods that reduce the dimensionality and complexity of the datasets and focus on recurring patterns, neglecting other information. Nevertheless, as Krippendorff (1989, p. 403) states, “replicable and valid inferences” can be drawn from a large amount of data, which would otherwise not be feasible.

The MASEM methodology used in Papers **III** and **VII** was limited by the so-called “apples and oranges” problem. This problem addresses the fact that the quantitative data that have been collected and meta-analyzed based on different papers with varying research designs and constructs could have affected the validity (Hwang, 1996). However, in **Papers III** and **VII**, the research question sufficiently narrowed the issue, and the samples and constructs were closely examined so that the conclusions rest on a homogeneous ground based on the inference goals (Hall *et al.*, 1994). Moreover, in meta-analyses, inferences are generated purely by quantitative data and thus neglect relevant qualitative data. Therefore, in the papers in question, the results were complemented by qualitative studies in the discussion of the results.

In the fsQCA approach in **Paper VI**, data were collected via a survey on Amazon’s Mechanical Turk. Ensuring data reliability and validity on this platform is challenging. However, guidelines were followed to determine appropriate participants and control and attention questions were used to control for validity (Hunt and Scheetz, 2019; Young and Young, 2019). In addition, data were tested for reliability, convergent validity, and discriminant validity. The fsQCA approach has recently gained increasing attention in IS literature for abductive research (Park, Fiss, *et al.*, 2020). Although an fsQCA is often used as the main method (e.g., Park *et al.*, 2017; Park, Pavlou, *et al.*, 2020; Park and Saraf, 2016), according to Ragin and Fiss (2008), it is particularly powerful as a complement to other quantitative or qualitative methods. Therefore, future work should complement the results with case studies and interviews as well as variance-based approaches.

Lastly, it is necessary to address the design science research limitations in **Paper I**. The developed artifact was based exclusively on meta requirements and design principles derived from problems described in the literature. Future work should account for the practical perspective of the problem space to confirm the problems or to derive further requirements. The evaluation design could confirm the effectiveness of the artifact based on technical parameters and the usefulness based on a survey but still lacked an intervention design with a control group to validate the impact of the tool compared to existing solutions. Future design science research evaluations should consider such a research design.

5 Conclusion

The quest for data-driven decision making is leading companies to AI-driven analytics to interpret their big data assets (Berente *et al.*, 2021; Rana *et al.*, 2021). The aim of this cumulative dissertation, including eight individual research contributions, was to provide theoretical underpinnings and empirical evidence of the capabilities required to effectively leverage and orchestrate resources related to AI-driven analytics in organizations, as well as to establish how and what business benefits can be derived from them. By operationalizing various technical, managerial, and organizational resources, this work concretized the implementation of AI in organizations and highlighted the complexity of orchestrating these resources for the effective deployment of AI. The effective utilization of these resources radiates to operational and strategic business performance in a wide range of sectors and, in particular, supports the performance enhancement of existing analytics use cases, which can result in business model innovation.

From the results, organizations can gain not only a more concrete conceptualization of AI-based analytics but also specific courses of action for the implementation of AI initiatives and an understanding of how they can impact business performance. With several theoretical implications, this dissertation expanded and empirically illuminated the foundation of a little explored field and identified several avenues for further research. Thus, the results of this work are a step toward scaling AI in organizations. As Chui et al. (2018, p. 29) stress, “[t]he question of how analytical techniques are scaling is driven less by the techniques themselves and more by a company’s skills, capabilities, and data.”

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Part B: Research Contributions

Paper I: Augmenting Humans in the Loop: Towards an Augmented Reality Object Labeling Application for Crowdsourcing Communities

Paper I	
Title	Augmenting Humans in the Loop: Towards an Augmented Reality Object Labeling Application for Crowdsourcing Communities
Authors	Julian Schuir René Brinkhege **Eduard Anton** Thuy Duong Oesterreich Pascal Meier Frank Teuteberg
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Abstract	Convolutional neural networks (CNNs) offer great potential for business applications because they enable real-time object recognition. However, their training requires structured data. Crowdsourcing constitutes a popular approach to obtain large databases of manually-labeled images. Yet, the process of labeling objects is a time-consuming and cost-intensive intensive task. In this context, augmented reality provides promising solutions by allowing an end-to-end process of capturing objects, directly labeling them and immediately embedding the data in training processes. Consequently, this paper deals with the development of an object labeling application for crowdsourcing communities following the design science research paradigm. Based on seven issues and twelve corresponding meta-requirements, we developed an AR-based prototype and evaluated it in two evaluation cycles. The evaluation results reveal that the prototype facilitates the process of object detection, labeling and training of CNNs even for inexperienced participants. Thus, our prototype can help crowdsourcing communities to render labeling tasks more efficient.
Identification	-
Link	https://aisel.aisnet.org/wi2021/QDesign/Track10/5/
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Paper II: The Humans Behind Artificial Intelligence – An Operationalisation of AI Competencies

Paper II	
Title	The Humans Behind Artificial Intelligence – An Operationalisation of AI Competencies
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Bibliographic information	Anton, E., Behne, A., and Teuteberg, F. (2020): The Humans Behind Artificial Intelligence – An Operationalisation of AI Competencies; in: Twenty-Eighth European Conference on Information Systems (ECIS 2020), A Virtual AIS Conference
Abstract	Despite the importance of artificial intelligence (AI) proficiency as a determinant for AI adoption, there remains a lack of empirical research studying competencies needed to leverage AI effectively. This paper addresses this research gap with a mixed methods approach. First, we conduct a qualitative content analysis of the practical and scientific literature to derive and structure the existing body of knowledge. We subsequently perform a quantitative content analysis of 9,247 job advertisements. We merge the results using a triangulation approach and a) present a comprehensive overview of key technical and managerial competencies essential for implementing and utilising AI on an individual level, b) highlight the demand for AI-related competencies in the three occupational fields Data Science and Engineering, Software Engineering and Development, and Business Development and Sales, and c) underline the need to adapt workforce competencies to a labour market transformation induced by AI.
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Paper III: Understanding the Operational Value of Big Data Analytics Capabilities for Firm Performance: A Meta-Analytic Structural Equation Modeling Approach

Paper III	
Title	Understanding the Operational Value of Big Data Analytics Capabilities for Firm Performance: A Meta-Analytic Structural Equation Modeling Approach
Authors	**Eduard Anton** Thuy Duong Oesterreich Frank Teuteberg
Publication outlet	Forty-Second International Conference on Information Systems (ICIS 2021)
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Bibliographic information	Anton, E., Oesterreich, T. D., and Teuteberg, F. (2021): Understanding the Operational Value of Big Data Analytics Capabilities for Firm Performance: A Meta-Analytic Structural Equation Modeling Approach; in: Forty-Second International Conference on Information Systems (ICIS 2021), Austin, USA.
Abstract	To uncover the key mechanisms of how value is created through big data analytics (BDA), our main research objective is to integrate prior empirical findings on the relationship between BDA capabilities and firm performance. We conducted meta-analytic structural equation modeling based on 271 correlations and 33,281 observations collected from 63 individual studies. The findings confirm that creating business value from BDA is a complex and dynamic process affected by various value creation mechanisms. Aside from direct relationships between BDA capabilities and firm performance, we highlight the mediating role of operational performance in the value transmission to market and financial performance. Our study contributes to the rising debate on the business value of BDA by providing an integrated and novel picture of the value-adding pathways emanating from BDA capabilities. This informs future information systems research on theory building and assists practitioners in effectively formulating their objectives of BDA initiatives.
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Paper IV: Augmenting the Future: An Exploratory Analysis of the Main Resources, Use Cases, and Implications of Augmented Analytics

Paper IV	
Title	Augmenting the Future: An Exploratory Analysis of the Main Resources, Use Cases, and Implications of Augmented Analytics
Authors	Thuy Duong Oesterreich **Eduard Anton** Feipeng Xu
Publication outlet	Twenty-Ninth European Conference on Information Systems (ECIS 2021)
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Bibliographic information	Oesterreich, T. D., Anton, E., and Xu, F. (2021): Augmenting the Future: An Exploratory Analysis of the Main Resources, Use Cases, and Implications of Augmented Analytics; in: Twenty-Ninth European Conference on Information Systems (ECIS 2021), A Virtual AIS Conference.
Abstract	Recently, augmented analytics has increasingly gained attention as one of the more advanced, novel approaches for handling big data. Based on machine learning and natural language processing, augmented analytics benefits from recent advancements in the artificial intelligence field to automate the analytics cycle. Despite the various benefits that augmented analytics offers for business and society, research on this topic is scarce to date. Based on the IT business value model, we examine the role of technological and social resources as well as the main use cases of augmented analytics. Therefore, we combine quantitative text mining with qualitative content analysis for an exploratory study of 350 academic and practical publications as well as 49 datasets of companies offering augmented analytics software and services. The findings contribute to the body of knowledge by enhancing the understanding of the augmented analytics concept, uncovering prevalent research gaps, and highlighting future research directions.
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Paper V: Business Model Taxonomy for Start-Ups in the Electric Power Industry – The Electrifying Effect of Artificial Intelligence on Business Model Innovation

Paper V	
Title	A Business Model Taxonomy for Start-Ups in the Electric Power Industry – The Electrifying Effect of Artificial Intelligence on Business Model Innovation
Authors	**Eduard Anton** Thuy Duong Oesterreich Julian Schuir Leslie Protz Frank Teuteberg
Publication outlet	International Journal of Innovation and Technology Management
Status	Published
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Bibliographic information	Anton, E., Oesterreich, T. D., Schuir, J., Protz, L., and Teuteberg, F. (2021): A Business Model Taxonomy for Start-Ups in the Electric Power Industry – The Electrifying Effect of Artificial Intelligence on Business Model Innovation; International Journal of Innovation and Technology Management, Vol. 18, No. 03, 2150004.
Abstract	Artificial intelligence (AI) serves as a technological driver for business model innovation by guiding decisions and automating services, thereby leveraging efficiency-enhancing and profitable business practices. Especially in the electric power industry, a multitude of start-ups have entered the market offering disruptive AI-based services. However, there has been little research to date on what concrete business models result from the diffusion of AI and how these might be classified. In view of this research gap, this paper contributes to a better understanding of start-ups in the electric power industry that use AI technologies by systematically developing a business model taxonomy. In addition, we conducted 12 semi-structured interviews with domain experts for the evaluation step and validated the robustness of the taxonomy based on cluster analysis to identify common business model archetypes. Finally, we derived and discussed the academic and practical implications of our research and highlighted future research avenues.
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Paper VI: Is Ethics Really Such a Big Deal? The Influence of Perceived Usefulness of AI-Based Surveillance Technology on Ethical Decision-Making in Scenarios of Public Surveillance

Paper VI	
Title	Is Ethics Really Such a Big Deal? The Influence of Perceived Usefulness of AI-Based Surveillance Technology on Ethical Decision-Making in Scenarios of Public Surveillance
Authors	**Eduard Anton** Kevin Kus Frank Teuteberg
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Bibliographic information	Anton, E., Kus, K., and Teuteberg, F. (2021): Is Ethics Really Such a Big Deal? The Influence of Perceived Usefulness of AI-Based Surveillance Technology on Ethical Decision-Making in Scenarios of Public Surveillance; in: Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS-54).
Abstract	So far, ethical perspectives have been neglected in empirical research focusing on the acceptance of artificial intelligence (AI)-based surveillance technologies on an individual level. This paper addresses this research gap by examining the individual moral intent to accept AI-based surveillance technologies deployed in public scenarios. After a thorough literature review to identify antecedents of moral intent, we surveyed n = 112 American participants in an online survey on mTurk and analyzed the data by using a fuzzy set qualitative comparative analysis. The resulting antecedent configurations provide insights into the inherent ethical decision-making process and thus contribute to a better understanding of the causality for accepting or rejecting AI-based surveillance technologies. Our findings emphasize in particular the influence of perceived usefulness of the technology on the ethical decision-making process.
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Paper VII: Painting A Holistic Picture of Trust in and Adoption of Conversational Agents: A Meta-Analytic Structural Equation Modeling Approach

Paper VII	
Title	Painting A Holistic Picture of Trust in and Adoption of Conversational Agents: A Meta-Analytic Structural Equation Modeling Approach
Authors	**Eduard Anton** Thuy Duong Oesterreich Julian Schuir Frank Teuteberg
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Bibliographic information	Anton, E., Oesterreich, T. D., Schuir, J., and Teuteberg, F. (2022): Painting A Holistic Picture of Trust in and Adoption of Conversational Agents: A Meta-Analytic Structural Equation Modeling Approach; in: Proceedings of the 55th Hawaii International Conference on System Sciences (HICSS-55).
Abstract	With their human-like nature, conversational agents (CAs) introduce a social component to human- computer interaction. Numerous studies have previously attempted to integrate this social component by incorporating trust into models such as the technology acceptance model (TAM) to decipher the adoption mechanisms related to CAs. Given the heterogeneity of these previous works, the aim of this paper is to integrate empirical evidence on the role and influence of trust within the nomological network of the TAM. For this purpose, we conduct a meta-analytic structural equation modeling approach based on 45 studies comprising k = 155 correlations, and N = 13,786 observations. Our findings highlight the multifaceted role of trust as a mediator transmitting the effects of the technology-related perceptions that drive the intention to use CAs. Our results present a comprehensive overview in a thriving research field that can guide both future theory building and the designs of more trustworthy CAs.
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Paper VIII: The Property of Being Causal – The Conduct of Qualitative Comparative Analysis in Information Systems Research

Paper VII	
Title	The Property of Being Causal – The Conduct of Qualitative Comparative Analysis in Information Systems Research
Authors	**Eduard Anton** Thuy Duong Oesterreich Frank Teuteberg
Publication outlet	Information & Management
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Bibliographic information	Anton, E., Oesterreich, T. D., and Teuteberg, F. (2022): The Property of Being Causal – The Conduct of Qualitative Comparative Analysis in Information Systems Research; Information & Management, Vol. 59, No. 3, 103619.
Abstract	Grounded in configuration and complexity theory, qualitative comparative analysis (QCA) combines the advantages of case-based and variable-oriented methods for rendering complex information systems (IS) phenomena comprehensible. Given its manifold benefits, the QCA method has attracted considerable attention in IS research, with an increasing number of studies employing it as their methodological approach. Based on a comprehensive review and synthesis of recent QCA practices from the IS field, covering 12 years of research, we outline the most prevalent research gaps and limitations concerning QCA's methodological application prior to identifying issues for further improvement as well as highlighting future research directions.
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