Designing and Managing Artificial Intelligence-Enabled Information Systems

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Abstract

Artificial Intelligence (AI) applications are said to have far-reaching potentials. While some organizations already lever AI technologies' potentials, others have not kept pace. Motivated by organizations' need to sustainably realize business value from AI-enabled IS, the aim of this thesis is to guide organizations in designing and managing AI-enabled IS.

I structured my thesis along three research goals (RG): identifying relevant organizational capabilities to lever AI technologies' potentials (RG1), guiding organizations in designing AI-enabled IS (RG2), and guiding organizations in managing AI-enabled IS (RG3). Approaching RG1, I derive organizational capabilities requirements to inform the organizational design and digital practices, frame the thesis' results, and shed light on issues that need (scientific) guidance (Essay 1). RG2 deals with guidance for organizations to foster preparatory capabilities, while RG3 addresses the realization capabilities. Besides informing the organizational design and digital practice by rigorously developed knowledge, this thesis provides several artifacts that scholars and practitioners can use. The introduced artifacts guide organizations in identifying AI use cases (Essay 2), deconstructing the creation of AI applications' business value (Essay 3), assessing the evolution of component technologies (Essay 4), managing AI applications (Essay 5), and measuring system risks (Essay 6).

My thesis provides novel theoretical perspectives on the identification of value-creating and value-capturing paths, their evaluation, their actualization, and management practices that sustain them. Accordingly, the essays provide theoretical lenses on, above all, the interplay between the technical and social subsystems of AI-enabled IS. The essays' relevance stems from providing design-oriented or management-oriented knowledge and the development of artifacts following the design science research paradigm.

Keywords: Artificial intelligence, machine learning, information systems, organizational design, practices, business value, value creation, value capture, management.

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Bayreuth, May 2021

Peter Hofmann

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Introduction to
Designing and Managing Artificial Intelligence-Enabled Information Systems

Abstract

This thesis aims to guide organizations in designing and managing Artificial Intelligence-enabled Information Systems (AI-enabled IS). It comprises six essays submitted to or published in renowned peer-reviewed journals or conference proceedings. By answering six dedicated research questions that I structured along three research goals, this thesis informs choices in organizational design and practices and provides artifacts, supporting organizations in designing and managing AI-enabled IS. In the introduction to this thesis, I motivate the essays overall context (Section 1), introduce and describe the characteristics of AI-enabled IS (Section 2), derive and motivate three research goals that structure my six essays (Section 3), introduce the essays' research methods (Section 4), summarize the essays' results (Section 5), and conclude and discuss this thesis' results, describe its limitations, and outline future research potentials (Section 6).

Keywords: Artificial intelligence, machine learning, information systems, organizational design, practices, business value, value creation, value capture, management.

Table of Contents – Introduction

1 Motivation

Ever since the development and application of artificial intelligence (AI) evolved from the theoretical realm and experiments in laboratory environments to real-use applications, AI has been a timely topic on corporate agendas. Among others, the maturing of machine learning (ML), the practical availability of data, and the reduction of application barriers such as affordable computing power are fueling AI applications' relevance for business (Jordan and Mitchell, 2015; LeCun et al., 2015). AI applications are said to have the potential to transform the characteristics of, among others, products or services, processes, work, or even business models (Brynjolfsson and McAfee, 2017; Cockburn et al., 2018; Faraj et al., 2018; Iansiti and Lakhani, 2020; Makridakis, 2017; Stone et al., 2016). Even when discounting the hype-fueled business expectations, examples from above all data-rich application areas such as web search or smartphone cameras indicate AI applications' real-world potentials (Brynjolfsson and Mitchell, 2017; LeCun et al., 2015). While the Go world champion's defeat by AlphaGo attracted much public attention (Silver et al., 2017), the de facto business value-creating but supposedly less spectacular breakthroughs sometimes slip into the background. For instance, an AI application automates data center cooling and industrial control, improving energy efficiency drastically (Gasparik et al., 2018). AI's application promises new ways to solve (existing) problems, resulting in new paths toward business value (Magistretti et al., 2019). Not engaging with AI technologies' potentials in detail poses either the risk of falling behind or wasting investments in pointless or even business-damaging initiatives.

While some organizations already use AI applications for specific tasks (Agrawal et al., 2018), others have not kept pace. Practical evidence indicates that AI initiatives often fail to live up to the anticipated potential to drive business value (Fountaine et al., 2019; Makarius et al., 2020; Ransbotham et al., 2019). Benbya et al. (2020) emphasized that most organizations have been unable to take their experimental pilot or proof-of-concept initiatives to the next phase (i.e., deployment in productive environments) and achieve little or no economic returns. However, the discrepancy between expectations of technologies' business potentials and de facto business value creation and capture is not new. For instance, big data and analytics initiatives – as a preceding technological and business momentum – are also underperforming against expectations (Grover et al., 2018). Adopting AI technologies comes with organizational, technical, and individual challenges (Baier et al., 2019; Bughin et al., 2017). Organizations would benefit from proactively addressing these challenges so as to make AI technology adoption more successful (Jöhnk et al., 2021). Motivated by organizations' need to sustainably realize AI applications' potentials, this thesis strives to guide IS scholars and IS practitioners in understanding and performing the managerial, methodological, and operational practices involved in designing and managing AI-enabled IS (Benbasat and Zmud, 2003). Accordingly, the thesis' overall research aim is as follows:

Guiding organizations in designing and managing AI-enabled IS.

This comes with multifaceted and fascinating questions for IS discourse whose answers bridge the gap between technological, organizational, and social issues. Thus, AI has become a central topic in IS discourse (Ågerfalk, 2020). By addressing this overall research aim, I respond to recent calls for IS inquiry into the AI field (Berente et al., 2019; Buxmann et al., 2019; Hinz et al., 2019; Rai et al., 2019). This thesis consists of six essays submitted to or published in renowned peer-reviewed journals or conference proceedings. In this way, I contribute to both my cumulative dissertation and the academic literature. This thesis informs choices in organizational design and digital practices and provides artifacts (e.g., methods and models), supporting organizations in designing and managing AI-enabled IS.

I have structured the remainder of the introduction to this thesis as follows: First, I introduce and describe the characteristics of AI-enabled IS (Section 2). I then derive and motivate three research goals (RGs) that structure my six essays (Section 3), introduce the essays' research methods (Section 4), and summarize the essays' results (Section 5). Finally, I conclude and discuss this thesis' results, describe its limitations, and outline future research potentials (Section 6). Following the introduction, you will find the essays' (extended) abstracts.

Since all the essays resulted from joint work with co-authors, I use the plural *we* when referring to the essays' content. In Appendix A, I describe the co-authors' contributions to the essays. The introduction to this thesis partly comprises content from the research articles. I have omitted the standard labeling of these citations so as to improve readability.

2 Conceptualizing Artificial Intelligence-Enabled Information Systems

AI is a research field whose characteristics and foci have evolved since pioneering work – such as Turing (1950) or McCarthy et al. (1955) – proposed their thoughts on creating intelligent machines.[1] Initially, McCarthy et al. (1955, p. 11) coined the research field's goal in a workshop proposal: "For the present purpose the artificial intelligence problem is taken to be that of making a machine behave in ways that would be called intelligent if a human were so behaving." Later, McCarthy (2007, p. 2) referred to AI as "the science and engineering of making intelligent machines, especially intelligent computer programs." While there is no consensual definition of AI, most definitions have similar structures: They understand AI as a research field's activities to create an artifact with characteristics that constitute intelligence. In more critical terms, "these definitions explain what AI research seeks to achieve, but they do not conclusively determine what AI is" (Rzepka and Berger, 2018, p. 3). For a detailed consideration of different definitions, I refer to the analysis and categorization of AI definitions in Russell and Norvig (2016). For this thesis' scope and purpose (i.e., guiding the design and management of AI-enabled IS), it is important to conceptualize the resulting artifact (i.e., AI-enabled IS). By referring to AI-enabled IS, I follow Rzepka and Berger (2018), subsuming both *AI-enhanced systems* (i.e., improving existing systems with AI technologies) and *AI-based systems* (i.e., developing new systems by means of AI technologies) under *AI-enabled systems*.

I will now introduce and describe the characteristics of AI-enabled IS so as to provide the necessary concepts on which the essays rely. I pay attention to the call by Ågerfalk (2020) to avoid confusing AI with related concepts such as machine learning, big data, and analytics. Similarly, Hawley (2019, p. 3) warned against using AI as a "marketing term chosen in recent years either intentionally or reluctantly, by those researchers who admit that 'statistics' garners the least amount of enthusiasm or 'buzz' from the

[1] Although this thesis does not elaborate on AI's historical development, I acknowledge the value of understanding the research field's origin. For more information on AI's historical development, I recommend Haenlein and Kaplan (2019), Russell and Norvig (2016), or Nilsson (2010).

general population, with 'machine learning' generating greater buzz, leading up to 'artificial intelligence' which may invite media frenzy."

To base my thesis' results on a comprehensive and solid conceptual foundation, I follow the notion of the IS artifact. Yet it is not my ambition to reignite the passionate discussion about the central artifact of IS research; I have used a conceptualization that is suitable for my inquiries (Ågerfalk, 2020; Alter, 2015; e.g., Alter, 2003; Baskerville et al., 2020; Benbasat and Zmud, 2003; Chatterjee et al., 2020; Faulkner and Runde, 2019; Orlikowski and Iacono, 2001). Relying on Chatterjee et al. (2020) has allowed me to take a sociotechnical perspective on the design and management of AI-enabled IS and to integrate the major theories and models used in the essays, i.e., the IT ecosystem model (Adomavicius et al., 2008, 2007), affordance-actualization theory (e.g., Nambisan et al., 2017; Strong et al., 2014), and information processing theory (Galbraith, 1973). Chatterjee et al.'s (2020) sociotechnical perspective has allowed me to elaborate both and the specifics of ISs' technical or social subsystem or their interplay in the superordinate system. Since it is primarily AI's technological characteristics that induce the essays' problematization, I specifically shed light on the technical subsystem (i.e., IT perspective), following a nested view that considers IT as part of IS (Alter, 2003). By unpacking the central artifact(s) in IS research into separate artifacts, I follow other scholars who have emphasized the interaction between these separate artifacts (e.g., Lee et al., 2015). El Sawy (2003) described three views of IT within IS: the connection view (i.e., IT as a tool used by people), the immersion view (i.e., IT integrated into the business environment), and the fusion view (i.e., IT is fused within the business environment). I follow the fusion view, in which "[p]eople work inside an IT-intensive environment where work processes and IT are inter-mingled, highly interdependent, and intimately influence one another" (El Sawy, 2003, p. 591).

I will now characterize AI from an IT perspective (Section 2.1) and an IS (Section 2.2) one.

2.1 Artificial Intelligence from an Information Technology Perspective

This thesis' essays benefit from an ecosystem view, which represents IT's complex, dynamic, and interdependent nature (Adomavicius et al., 2008, 2007). Thereby, technology can be any means to serve a human purpose (Arthur, 2007). Adomavicius et al. (2008, p. 783) defined an IT ecosystem as "a subset of information technologies in the IT landscape that are related to one another in a specific context of use." In this way, I take up the long tradition of recognizing technology's systemic nature (Adomavicius et al., 2012; Arthur, 2009; Rosenkopf and Nerkar, 1999). In their hierarchical understanding of technologies' roles, IT can act as a component, a product and application, or infrastructure (Adomavicius et al., 2008, 2007; Rosenkopf and Nerkar, 1999). IT's component role allows one to describe technologies as assemblies of component technologies that themselves can consist of subordinate component technologies or assemblies (Adomavicius et al., 2008; Arthur, 2007). While products and applications, which consist of component technologies, provide functions to users, infrastructure complements a product's or an application's use in a specific context (Adomavicius et al., 2008). I summarize my understanding of IT's systemic nature in Figure 1.

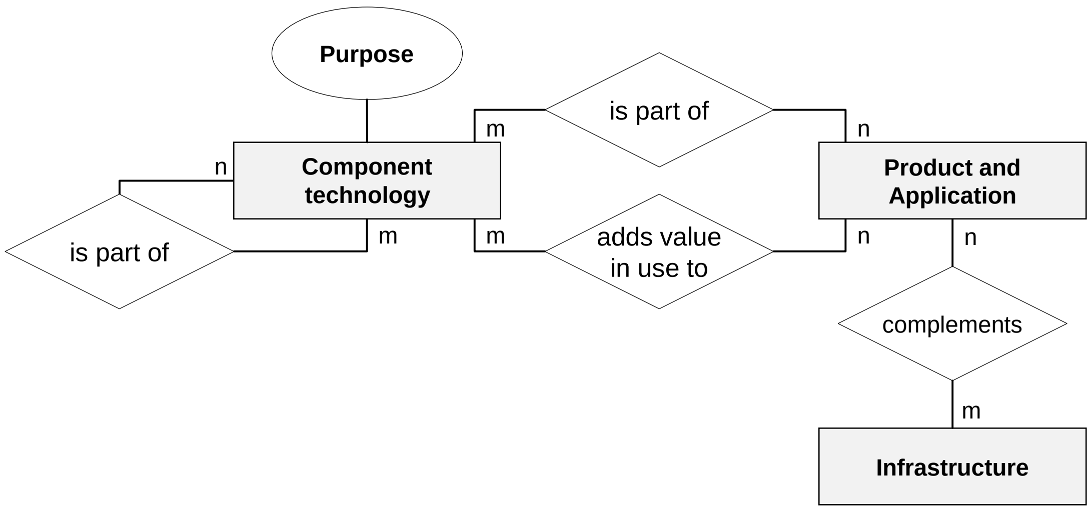

Figure 1. Understanding IT's Systemic Nature

Referring to AI's definition (e.g., McCarthy, 2007), I affirm that it is not a set of technologies but their purpose (i.e., making machines intelligent) that characterizes this research field. Thus, one could think of AI technologies as technologies that seek to add value in use to a product or application by behaving intelligently. This understanding is in line with Stone et al. (2016), who referred to AI as a set of computational technologies. Thus, the definition of AI technologies' purpose does not imply a specific problem, as is common in other fields such as computer vision (Demlehner et al., 2021). Since AI technologies such as artificial neural networks may be suitable to solve many different yet specific problems, they assume the characteristics of a general-purpose technology (e.g., Brynjolfsson and Mitchell, 2017; Klinger et al., 2018; Magistretti et al., 2019).

However, there is no consensus against which to compare the degree of intelligent behavior (e.g., human intelligence, rationality, status quo of computational abilities) (Rich, 1983; Russell and Norvig, 2016). The referential challenge in describing (artificially) intelligent behavior manifests itself, among others, as follows: On the one hand, some problems are challenging for humans but relatively easy for computers to solve (e.g., mathematical equations). On the other hand, some problems are challenging for computers but easy for humans to solve (e.g., contextual understanding). Accordingly, "machines can already do things only humans used to do, and in some very specific tasks even outperform us" (Ågerfalk, 2020, p. 2). Based on the restrictiveness of AI applications' capabilities, one may further distinguish between weak and strong AI (also known as *artificial narrow intelligence* and *artificial general intelligence*). While there is at least some consensus that weak AI applications can only solve specific tasks, the research lacks common ground on what would constitute a strong AI application (Kurzweil, 2005; Russell and Norvig, 2016). To escape AI applications' definitional dilemma, one can rely on the idea that specific capabilities demand intelligence. These include problem-solving, reasoning, knowledge representation, learning, planning, perceiving, acting, communication, and natural language processing (Russell and Norvig, 2016). Thus, some scholars follow a cognitive function lens that allows one to describe AI's capabilities (Hofmann et al., 2020b; Rai et al., 2019; Stohr and O'Rourke, 2021; Wang et al., 2006).

Following Adomavicius et al.'s (2008) IT ecosystem view, and in line with the cognitive function lens, I understand AI-enabled applications as an assembly of technologies that provide cognitive functions' value to users. The assembly of technologies instantiates in parallel arranged or sequentially arranged component technologies and may be complemented by infrastructure. For instance, a conversational agent could use subsequently arranged technology assemblies to (1) perceive the audio signal, (2) interpret the question, (3) answer the question, and (4) generate the response (Allen et al., 2001). There are various component technologies to approach artificially intelligent behavior, including connectionism approaches such as artificial neural networks (Jordan and Mitchell, 2015; LeCun et al., 2015) or symbol systems (Haugeland, 1985). Currently, ML is the dominant approach to AI (Ågerfalk, 2020; LeCun et al., 2015). In his empirical study, Basole (2021) characterized the growing ecosystem of – often open-source – ML methods as a complex networked system. However, AI-enabled applications may rely not only on technologies typically associated with approaching AI; promising potentials also exist for assemblies that include technological approaches such as blockchain (Guggenberger et al., 2021; Karger, 2020; Salah et al., 2019) or mixed reality (e.g., Kanda et al., 2018).

In sum, AI-enabled applications characterize applications that perform cognitive functions regardless of their specific technology assembly.

2.2 Artificial Intelligence from an Information Systems Perspective

I will now describe my conceptualization of AI-enabled IS. I summarize this conceptualization in Figure 2.

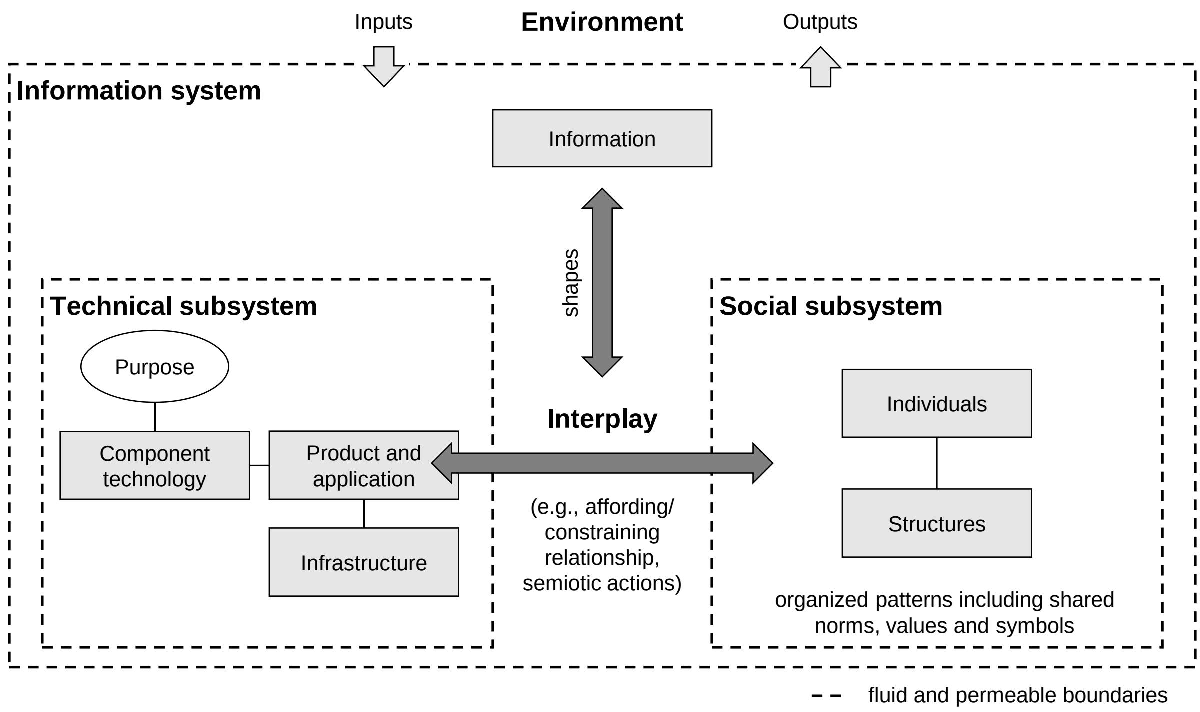

Figure 2. Artificial Intelligence-Enabled Information Systems from an Information Systems Perspective, based on Chatterjee et al. (2020, p. 7)

Based on sociotechnical thinking (Sarker et al., 2019), an IS is “a superordinate system composed of social and technical subsystems, with information playing a key role that captures the state and behavior of these superordinate systems” (Chatterjee et al., 2020, p. 7). The social subsystem comprises individuals, structures, and their relationships, forming organized patterns that include shared norms, values, and symbols (Allon and Hanany, 2012; Chatterjee et al., 2020; Lee et al., 2015). Chatterjee et al. (2020) followed Sykes et al. (2014, p. 54), who specified the components of a technical subsystem as “devices, tools, and techniques needed to transform inputs into outputs in a way that enhances the […] performance of the organization.” Referring back to the nested (i.e., hierarchical) view of IT and IS, the technical subsystem’s conceptualization is compatible with Adomavicius et al.’s (2008, 2007) IT ecosystem model. The IT ecosystem model helps my thesis with a more detailed view of AI technologies’ technical specificities. The social and the technical subsystems emerging within changing contextual conditions and mechanisms are open systems with fluid and permeable boundaries, allowing them to interact with their surrounding environment (Chatterjee et al., 2020; Wynn and Williams, 2012). Ågerfalk (2020) also emphasized the interconnectedness of IS that instantiate, for instance, in AI platforms that provide organizations a gateway toward creating or using AI applications (Geske et al., 2021; Rai et al., 2019).

A substantial element of Chatterjee et al.’s (2020) conceptualization is the interplay between the technical and the social subsystem. In my view, there are various perspectives that one could take to analyze the interplay between the technical and social subsystems and accordingly answer relevant questions of AI-enabled IS or their management. For instance, Chatterjee et al. (2020) elaborated on the interplay between technical and social subsystems from an affording-constraining and information perspective. While I refer to Section 2.2.1 for a more detailed elaboration on the affording-constraining relationship and to Section 2.2.2 for information’s role, I will now briefly discuss how a semiotic perspective on the interplay between the technical and the social subsystems is compatible and beneficial for inquiring into AI-enabled IS. From a semiotic perspective, ISs can be characterized as active mediators of social action and interaction that handle both data and meaningful symbols (Ågerfalk, 2020; Goldkuhl and Ågerfalk, 2005). Semiotic systems have semiotic symbol processing capabilities (i.e., manipulating symbols as well as affording interpretation and communication) that empowers them to act as digital agents on behalf of persons and organizations (Aakhus et al., 2014; Ågerfalk, 2020, 2004; Beynon-Davies, 2016; Stamper et al., 2000). This semiotic view is suitable when conceptualizing AI applications as intelligent agents that autonomously perceive and act in their environment (Bawack et al., 2019; Russell and Norvig, 2016). Thus, intelligent agents have a self-governing capability (Tschang and Mezquita, 2020) and can therefore actively participate and communicate within the IS.

To foster understandability, I apply the conceptualization to computer-aided detection (CADe) systems as an exemplary AI-enabled IS, as illustrated in Figure 3. In this example, medical staff follows defined processes to use a CADe system that relies on an artificial neural network and other component technologies. The artificial neural network's purpose is to detect lung nodules on thoracic CT images (Armato et al., 2001).

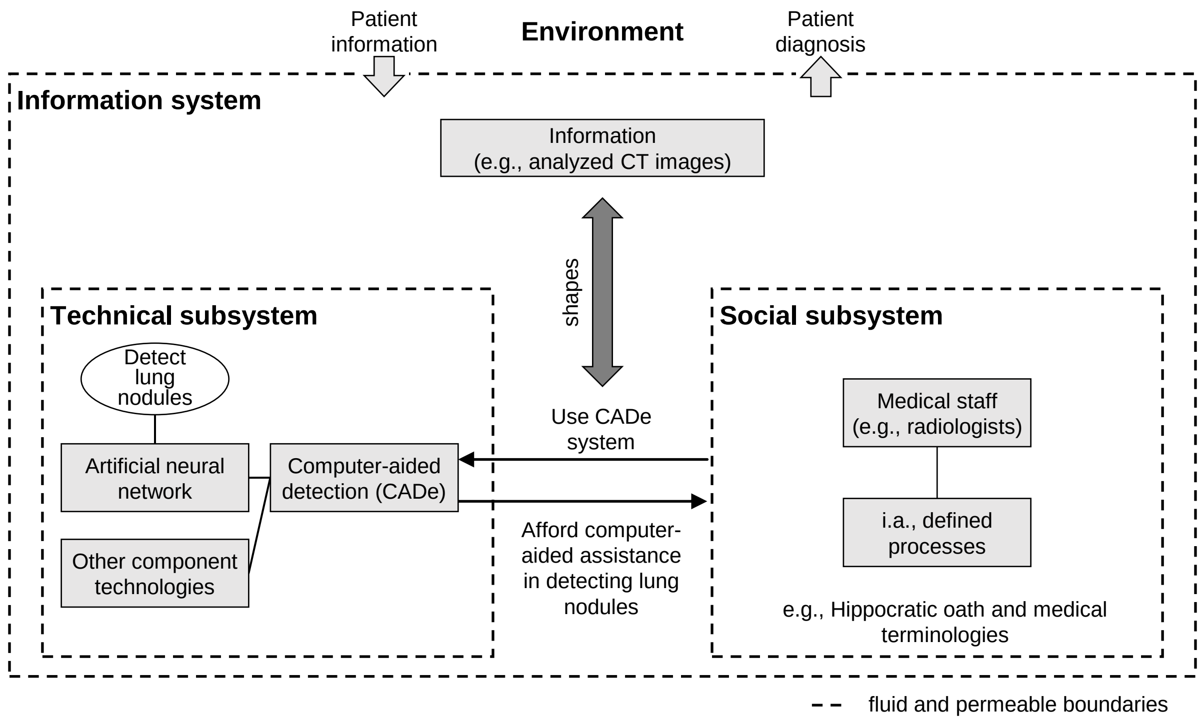

Figure 3. Computer-Aided Detection Systems as an Exemplary Artificial Intelligence-Enabled Information System

2.2.1 Affording and Constraining

In this section, I will explain the affording-constraining relationship between the social and the technical subsystems in some detail. As introduced in Gibson's (1979) seminal work on visual perception, affordances describe the action possibilities that emerge from the relationship between an object and an observer, and can either enable or constrain. Although initially conceived for ecological psychology, affordance theory's properties (e.g., affordances' mere existence does not guarantee outcomes and the emphasis on the object-observer relationship) gained popularity across domains (Keller et al., 2019; Stoffregen, 2003). Among others, IS scholars adapted the idea of affordances for their inquiries (e.g., Dremel et al., 2020; Du et al., 2019; Leonardi, 2013). In light of IS research, affordance theory denotes action possibilities stemming from technologies as technology affordances (Leidner et al., 2018; Tim et al., 2018). Majchrzak and Markus (2012, p. 1) defined a technology affordance as "what an individual or organization with a particular purpose can do with a technology." Thus, the relationship between an actor and a technology establishes a technology affordance and not solely technology features (Majchrzak and Markus, 2012; Nambisan et al., 2017; Strong et al., 2014; Volkoff and Strong, 2013). I will henceforth use *affordance* as a synonym for technology affordance so as to enhance readability.

By introducing the affordance-actualization theory, Strong et al. (2014) enhanced affordance theory with an organizational perspective. By following affordance-actualization theory, I distinguish between affordances, their actualization, and outcomes (Leidner et al., 2018; Nambisan et al., 2017; Strong et al., 2014; Tim et al., 2018). While affordances represent the relationship between technologies and actors, their actualizations are "goal-oriented actions taken by actors as they use a technology to achieve an outcome" (Du et al., 2019, p. 53). This thesis' essays follow other scholars who use affordance theory inquiries to consider a user group or the entire organization (Du et al., 2019; Markus and Silver, 2008; Strong et al., 2014; Zammuto et al., 2007).

AI technologies' characteristics as general-purpose technology afford numerous action possibilities for creating value. Value creation scenarios range from AI-enabled data analysis and full process automation to intelligent products and services (Coombs et al., 2020; Davenport and Ronanki, 2018; Tarafdar et al., 2019). While the application of AI initially centered around automating linear, stepwise, sequential, and repeatable tasks, organizations began to consider the automation of nonsystematic cognitive tasks and human-machine collaboration (Benbya et al., 2020). To create and sustain the value of applying AI, organizations should consider the whole spectrum of AI's capabilities to automate or augment human work (Raisch and Krakowski, 2020). However, mere awareness of AI technologies' action possibilities is not enough. Organizations need the capability to situate them in their organizational context (Alsheibani et al., 2018; Pumplun et al., 2019). There are hurdles to overcome when creating and capturing business value by means of AI applications. These hurdles may be organization-specific and include utility-restricting hurdles (e.g., limited explainability of artificial neural network outcomes), ethical, legal, or social hurdles (e.g., privacy regulations), and functional hurdles (e.g., dependence on the availability of appropriate data) (e.g., Baier et al., 2019; Hummer et al., 2019; Kelly et al., 2019; Leotta et al., 2019; Sun and Medaglia, 2019; Yu et al., 2018).

For this thesis' essays (Essays 2 and 3), affordance-actualization theory serves as a suitable theoretical lens to analyze what AI applications can afford goal-oriented actors in their organizational context. Thus, the thesis benefits from affordance-actualization theory, as it is in line with contextualization in IS research. Contextualization emphasizes the need to "stay in touch with the practical context in which information systems are used" and to "not assume that technologies will work the same or be ascribed the same meaning in all contexts." (Ågerfalk, 2020, p. 5).

2.2.2 Information Processing Needs and Capabilities

In Chatterjee et al.'s (2020, p. 13) notion of an IS artifact, "information provides some sort of order to a goal-seeking system in its effort to realize those goals" (Chatterjee et al., 2020, p. 13). When researching AI-enabled IS, it is important to distinguish between data and information. Since information is data with a context-providing model (Bakopoulos, 1985), information needs to be meaningful and well-formed data (Floridi, 2009). For instance, messages from within the organization or its environment can carry intentions by embedding data into socially meaningful units (Ågerfalk, 2020). For the relationship between information to knowledge, I refer to Alavi and Leidner (2001). For instance, Hofmann et al. (2021b) described how data-driven application capabilities foster transforming data to information and information to knowledge. Information is essential in IS to reduce uncertainty or the entropy of the superordinate system (Chatterjee et al., 2020).

Accordingly, information processing theory, which is centered around the need to reduce uncertainty (Galbraith, 1973), is beneficial for analyzing AI-enabled IS. Information processing theory describes three interdependent concepts: information processing needs, information processing capabilities, and their fit (Galbraith, 1973). While the degree of uncertainty determines information processing needs (Zack, 2007), information processing capabilities reduce them (Galbraith, 1973). Thereby, different mechanisms (e.g., structural, process, and IT mechanisms) exist for developing information processing capabilities (Bensaou and Venkatraman, 1995; Zack, 2007). Since the fit between information processing needs and capabilities determines an organization's performance, organizations should aim to attain such a fit (Daft and Lengel, 1986; Galbraith, 1973; Premkumar et al., 2005).

In this thesis, information processing theory allowed me to identify relevant information processing capabilities for developing, training, and deploying ML applications (Essay 2) and to explain management's capability to reduce uncertainty by identifying problems and aligning them with management's objectives.

3 Thesis Structure and Research Goals

Based on the overall research aim (i.e., guiding organizations in designing and managing AI-enabled IS), I derived three specific research goals:

(RG1) *Identifying relevant organizational capabilities to lever AI technologies' potentials*

(RG2) *Guiding organizations in designing AI-enabled IS*

(RG3) *Guiding organizations in managing AI-enabled IS.*

While RG1 takes a comprehensive organizational capabilities perspective to guide organizations in levering AI technologies' potentials, RG2 and RG3 address selected organizational capabilities in some depth. Thus, the inquiry of RG1 not only informs choices in organizational design and practices, but ensures that the results of RG2 and RG3 enhance relevant organizational capabilities. Both RG2 and RG3 follow a value-oriented perspective to ensure the sustainable creation of business value. RG2 elaborates on the identification, evaluation, and actualization of AI's affordances to guide the business value-enhancing design of AI-enabled IS. RG3 elaborates on sustaining AI-enabled IS's business value through managerial guidance (RG3). By focusing on the sustainable creation of business value, I address an established IS research stream (Chau et al., 2007; Melville et al., 2004; Schryen, 2013).

When doing my inquiries, I sought both rigor and (practical) relevance. Thus, I acknowledge the need for IS research that contributes to the academic discourse by rigorously answering relevant research questions and that makes real-world impacts by providing useful artifacts or knowledge (Agarwal and Lucas, 2005; Benbasat and Zmud, 1999; Iivari, 2003; Nunamaker et al., 2017; Te'eni et al., 2017). I refer to Section 1 for a motivation of the overarching relevance of applying AI technologies in business. To ensure my research questions' relevance, I considered "the particularities of each technological development […] to fully capture the interdependencies that develop between them" (Mikalef et al., 2018, p. 548). Considering these particularities has allowed me to concentrate on AI technologies' specifics. Accordingly, I rely on existing knowledge whenever possible and only create new knowledge whenever particularities require it.

In this thesis' scope, particularities affect the value-creating and value-capturing path of AI-enabled IS or its accompanying managerial, methodological, and operational practices. My research questions mainly source particularities in the technical subsystem and its interplay with the social subsystem (e.g., AI technologies' characteristic as a general-purpose technology, ML components' progressing capabilities, or the limited explainability of artificial neural networks' results). If the answer to a research question was not specific to the particularities that motivate this question, we considered the next higher level of analysis. I will now describe the research gaps and research questions for each essay following the three RGs.

I provide an overview of the essays in Table 1. For my other publications, please see Appendix B.

Table 1. Essays Addressing the Thesis' Three Research Goals

RG	Title
RG1: Identifying relevant organizational capabilities to lever AI technologies' potentials	**Essay 1:** What Got You Here Will (Not) Get You There: Rethinking Organizational Capabilities for Machine Learning
RG2: Guiding organizations in designing AI-based IS	**Essay 2:** The Efficacy of Methodological Guidance for Identifying, Evaluating, and Actualizing AI's Affordances: Revelations from a Project at EnBW Building upon: Hofmann et al. (2020b)
	Essay 3: Opening the Black Box of Artificial Intelligence's Business Value: Toward an Effect Path Model
	Essay 4: Inter-Technology Relationship Networks: Arranging Technologies through Text Mining (Hofmann et al., 2019)
RG3: Guiding organizations in managing AI-based IS	**Essay 5:** How to Manage Artificial Intelligence Applications in Healthcare: Introducing the AIAMA Model
	Essay 6: How Ill is Your IT Portfolio? Measuring Criticality in IT Portfolios Using Epidemiology (Guggenmos et al., 2019)

3.1 RG1: Identifying Relevant Organizational Capabilities to Lever Artificial Intelligence Technologies' Potentials

To realize business value from AI technologies, organizations may well need to adapt their resource base (Gupta and George, 2016; Nambisan, 2017; Ritter and Pedersen, 2020). While an organization's established resource base allowed it to lever known technologies, it remains unclear whether organizations have the necessary capabilities to lever AI technologies. However, without knowing how new technological characteristics change organizational capabilities requirements, it is left to chance how organizations succeed in adopting AI (Jöhnk et al., 2021). Accordingly, organizations require a comprehensive understanding of the necessary capabilities set, since lacking or weak capabilities may not only limit an organization in its levering of AI technologies' full potentials but may even result in value destruction (Canhoto and Clear, 2020). As the most relevant technological approach to AI (Jordan and Mitchell, 2015; LeCun et al., 2015), it is crucial to shed more light on ML-induced organizational capabilities requirements. Rethinking capabilities requirements is relevant, because it removes blind spots for organizations' ML adoption and encourages the sustainable development of a capabilities set. Further, understanding the organizational capabilities requirements informs future research in shedding more light on where organizations need guidance. However, the research has lacked a thorough investigation of relevant capabilities for successfully developing, training, and deploying ML applications. Thus, we ask:

Which capabilities set does an organization need to successfully lever ML? (Essay 1)

3.2 RG2: Guiding Organizations in Designing Artificial Intelligence-Enabled Information Systems

AI technologies' affordances are a mixed blessing for organizations. In their executive study, Ransbotham et al. (2019, p. 1) found that "a growing number of leaders view AI as not just an opportunity but also a strategic risk." For one thing, levering AI applications' potentials may lead to a new source of competitive advantages. For another thing, AI applications' anticipated potentials and the fear of falling behind may also pressure organizations to adopt AI, even if they do not face an acute problem. Although a general-purpose technology such as an AI technology may help spur innovation (Bresnahan and Trajtenberg, 1995), suitable use cases are not always immediately obvious (Jovanovic and Rousseau, 2005). Accordingly, there is a need to guide organizations in designing AI-enabled IS (i.e., RG2). Since AI's technological potentials are not limited to specific problems or tasks, organizations face challenges in identifying, evaluating, and actualizing AI technologies' affordances (i.e., identifying AI use cases). The identification of AI use cases should allow for economic exploitation and should consider the organizational context (Alsheibani et al., 2018; Hofmann et al., 2020b; Pumplun et al., 2019). Driven by the lack of clarity regarding AI technologies' specific added value, organizations sought to clarify their response to AI technologies' general potentials. While technology selection approaches are common in practice, they reach their limits when levering the potentials of technologies, such as AI technologies, whose purpose is problem-independent. Researchers have recently developed new methods to identify use cases that – given a technology – seek the fitting problem (e.g., Fridgen et al., 2018; Hofmann et al., 2020b; Sturm et al., 2021). For instance, Hofmann et al. (2020b) introduced a method to identify organization-specific AI use cases by adopting method chunks that range between social constructivism and technology determinism. However, the research lacks a solid understanding of their efficacies and the factors that influence efficacy. This leads to uncertainties regarding the research results' relevance for practice. In contrast, we pursue the following research objective: We seek to investigate methodological guidance's efficacy to identify, evaluate, and actualize AI technologies' affordances. We approached this objective with the following questions:

1) Is the method efficacious? 2) Why is the method (not) efficacious? 3) How can we make the method more efficacious? (Essay 2)

When preparing for or retrospectively evaluating the goal-oriented realization of AI use cases' potentials, organizations need to reflect on where and how AI generates business value (Burton-Jones and Volkoff, 2017). Thus, organizations need to understand how the actualization of AI technologies' technological possibilities leads to business value (Krancher et al., 2018; Leidner et al., 2018). However, when modeling AI applications' business value contributions, organizations face two major challenges: AI technology's characteristics as a general-purpose technology resulting in a diversity of technological capacity confronts organizations with diverse possible application scenarios (Brynjolfsson et al., 2017; Frank et al., 2019; Hofmann et al., 2020b; Magistretti et al., 2019). Second, organizations need to interweave AI technologies' affordances with their organizational context according to their business objectives (Buxmann et al., 2019; Canhoto and Clear, 2020). Accordingly, organizations need to bridge business imagination and the understanding of technological potentials to evaluate how AI technologies' affordances provide business value (Grønsund and Aanestad, 2020; Krogh, 2018; Pumplun et al., 2019). However, the literature has lacked a theoretical and model-based consideration of the actualization of AI technologies' affordances as well as an evaluation of their impacts on business value (Du et al., 2019; Strong et al., 2014). Filling this research gap would help actualize AI technologies' affordances, improving value-based decision-making (Grover et al., 2018). To our best knowledge, no model or framework exists that depicts the value-creating and value-capturing path of AI use cases in organizations. To address this research gap, we ask:

How to model AI applications' realization of business value from data? (Essay 3)

The identification and evaluation of AI technologies' affordances confront organizations with the decision which of the many technologies are worth adopting, developing, or examining more closely. Thus, organizations must understand the dynamic IT ecosystem of interrelated technologies (Adomavicius et al., 2008). An IT ecosystem perspective accounts for the innovation potentials that arise from the recombination of existing technology components or modules (Fleming and Sorenson, 2001; Schoenmakers and Duysters, 2010). However, forecasting technological advances and trends is challenging (Adomavicius et al., 2007; Daim et al., 2006). A promising approach is to extract relevant information from technology-related documents such as patent documents using Text Mining techniques (Gupta and Pangannaya, 2000; Lee et al., 2009; Madani and Weber, 2016; Nakamura et al., 2015). Some researchers refer to Text Mining's application to technology management purposes as Tech Mining or Technology Mining (Madani, 2015; Porter and Cunningham, 2005). The literature already provides techniques to arrange technology-related entities in structured representations (e.g., graphs, networks, or maps) (Engelsman and Van Raan, 1994; Yoon and Park, 2004). However, it lacks a Text Mining method that can accomplish the following requirements: a) For purposefully investigating technologies, the Text Mining method should be able to systematically arrange predeterminable technologies or abstractions of these. b) For examining the evolution of IT ecosystems, the Text Mining method should be able to trace patterns of technological change in a thorough longitudinal analysis. c) For incorporating the greatest variety of possible technology-related information in the analysis, the Text Mining method should be able to incorporate information from different sources. To develop a Text Mining method that fulfills these requirements, thereby closing a research gap, we ask:

How can an analytical method using Text Mining techniques be developed that arranges predefined technologies into a dynamically interpretable inter-technology relationship network? (Essay 4)

3.3 RG3: Guiding Organizations in Managing Artificial Intelligence-Enabled Information Systems

To sustainably create and capture the business value of AI-enabled IS, organizations require comprehensive managerial capabilities. Some even state that "the introduction of AI is associated with significant changes in how organizations are managed." (Benbya et al., 2020, p. xvi). The progressing actualization of AI technologies' affordances puts application management under increasing pressure to develop capabilities to manage AI applications in the organization. Among the most promising domains are research endeavors in healthcare, which promise concrete opportunities to lever AI technologies (Gilvary et al., 2019; Yu et al., 2018). After years of research, organizations are now starting to capture AI technologies' value creation potentials with market-ready AI applications (Garbuio and Lin, 2019). However, AI applications management is a dynamic process that constantly poses new challenges throughout the organization and calls for new coordination and control mechanisms (Benbya et al., 2019; Faraj et al., 2018). Thus, there is a need to guide AI application management to enable organizations to cope with challenges stemming from deployed AI applications (Ananny and Crawford, 2018; Diakopoulos, 2015). Without understanding the challenges that arise from AI applications' deployment, organizations face the risk of AI applications failing in real-world settings (Higgins and Madai, 2020; Pumplun et al., 2021). Accordingly, organizations should manage AI applications thoroughly if they are to successfully contribute to the healthcare field (Shaw et al., 2019; Yu and Kohane, 2019). To date, the literature has only described AI application challenges; it has rarely addressed practices that solve the shortcomings in deploying and operating AI applications (Baier et al., 2019; Hummer et al., 2019).

However, reliably deploying and operating AI applications requires organizations to master these challenges (Hague, 2019; Higgins and Madai, 2020; Shaw et al., 2019; Yu and Kohane, 2019). Considering the complex healthcare system, which consists of multiple parties and diverse interrelationships, it often remains unclear how healthcare organizations should manage AI applications. Thus, we ask:

How to manage AI applications in healthcare? (Essay 5)

For the implementation of new technologies (e.g., the deployment of AI applications), IT projects have critical roles in organizations. Thus, IT projects can become complex owing to interdependencies in an IT project portfolio (ITP) and their embedding in the IT landscape (e.g., other applications). The many different interdependencies make it difficult for humans to consider all the dependencies, potentially resulting in the disregarding of cascading failures. Due to the black-box characteristic of some ML applications, this circumstance is especially prevalent when deploying new ML applications or integrating new applications into IT landscapes with ML applications. Thus, decision-supporting methods that measure systemic risks can help to guide practitioners. This guidance could allow practitioners to bring their experimental pilot or proof-of-concept initiatives into productive environments. For measuring criticality in ITP, previous research considered ITPs as complex networks (Beer et al., 2015; Guo et al., 2019; Neumeier et al., 2018; Radszuwill and Fridgen, 2017; Wehrmann et al., 2006; Wolf, 2015). However, the research has focused mainly on direct dependencies, neglecting systemic risk's impacts owing to indirect dependencies. Thus, popular portfolio risk measures (e.g., portfolio variance) or centrality measures (e.g., degree centrality, closeness centrality, or betweenness centrality) are unsuitable in the ITP context. More recently, researchers have begun to consider indirect dependencies. For instance, Wolf's (2015) approach, which uses alpha centrality, provides significantly better results than the abovementioned approaches. Nonetheless, even this approach has a weakness: it does not consider how rapidly a failure spreads from one IT project to another, or to an IT asset. However, propagation speed affects an organization's ability to avert damage and, therefore, determines IT projects' criticality. Among others, epidemiology already uses network diffusion models to quantify cascade effects, paying attention to propagation speed (e.g., Brockmann and Helbing, 2013; Kermack and McKendrick, 1927). Owing to the overlap in requirements for risk measures in epidemiology and ITP management (e.g., negative effects of dependencies, or propagation speed's importance), we assume that we could learn from transferring and applying methods from epidemiology. Among the epidemiology approaches, Kermack and McKendrick's (1927) susceptible-infected model (SI model) is probably the best-known model for simulating the spread of disease. Thus, we ask:

What can we learn from transferring and applying the SI model from epidemiology to complex IT portfolios? (Essay 6)

4 Research Methods

I will now briefly outline the expediency and execution of the essays' research methods as summarized in Table 2. A detailed description can be found in the essays.

Table 2. The Six Essays' Research Methods

RG1: Identifying relevant organizational capabilities to lever AI technologies' potentials	
Essay 1	**Qualitative exploratory research** • Analyzing the literature to collect justificatory knowledge and draft an initial framework • Categorical and selective coding of 54 interviews with ML experts from the podcast series *AI in Business* (Faggella, 2020) to refine the framework • Substantiating the interview findings with further literature and integrating them into established theoretical reasoning
RG2: Guiding organizations in designing AI-based IS	
Essay 2	**Clinical research** • Intervening in organizational practices (i.e., applying and advancing Hofmann et al.'s (2020b) method at EnBW) • Collecting and analyzing case data (e.g., the project diary, photos that summarize workshop results, and process models)
Essay 3	**Design science research** • Analyzing the literature to derive design requirements and inform the illustrative scenario (using AI applications in manufacturing) • Iteratively designing and evaluating the artifact in three stages using an illustrative scenario, logical argument, action research, and expert evaluation
Essay 4	**Design science research** • Analyzing the literature to identify Text Mining techniques (i.e., method chunks) and collect justificatory knowledge • Executing an assembly-based process model for situational method engineering to combine the method chunks • Demonstrating the method's ease of use and feasibility by instantiating and applying it to an exemplary scenario • Evaluating the method's effectiveness against human judgment and face validity
RG3: Guiding organizations in managing AI-based IS	
Essay 5	**Qualitative exploratory research** • Deriving the management challenges of AI applications in healthcare from the literature • Iteratively developing the AIAMA model • Conducting an expert study to evaluate and refine the AIAMA model and discuss managerial recommendations • Applying the AIAMA model to the derived management challenges to draw model-based managerial recommendations • Synthesizing the managerial recommendations
Essay 6	**Design science research** • Analyzing the literature to collect justificatory knowledge • Iterating the relevance, design, and rigor cycles starting with Kermack and McKendrick's (1927) SI model • Instantiating and applying the method to real-world data • Evaluating the method's effectiveness against human judgment and alpha centrality

In Essay 1, we conducted qualitative exploratory research to derive a capabilities framework for ML (CFML) in four steps: In step 1, we collected justificatory knowledge on relevant or associated capabilities (i.e., IT, digital, and big data analytics capabilities) following Jesson et al.'s (2011) guidelines for literature analysis. We used the gained knowledge to draft the initial version of our framework, which structures the literature-based insights according to typical organizational layers affected by digital innovations (Urbach and Röglinger, 2019). In steps 2 and 3, we sought to better understand ML's specifics and their implications for capabilities requirements by transcribing and analyzing 54 interviews with ML experts from the podcast series *AI in Business* (Faggella, 2020). In step 2, we conducted categorical coding to extract relevant ML capabilities from the interviews (Saldaña, 2009) and reworked our initial CFML based on new insights. In step 3, we conducted selective coding based on the adjusted categories and subcategories from the revised framework (Saldaña, 2009). The gained insights allowed us to further improve the CFML. In step 4, we substantiated our interview findings with further literature and integrated our findings into established theoretical reasoning (i.e., information processing theory and resource orchestration view) (Galbraith, 1973; Sirmon et al., 2007).

In Essay 2, we investigated methodological guidance's efficacy for identifying AI use cases in a clinical research setting. Specifically, we applied and advanced the method for identifying AI use cases introduced by Hofmann et al. (2020b). In clinical research from IS practice, intervention in organizations' practices drives the inquiry, seeking to translate theory-based knowledge into immediate practical outcomes (Lenfant, 2003; Schein, 1995). Since clinical research from IS practice is not yet established, we draw on the parallels to clinical research in the medical domain (Hulley et al., 2013). To report extensive experiences and insights from the method's application in practice, we intervened in organizational practices during a six-month project at EnBW Energie Baden-Württemberg AG (EnBW), one of Europe's largest energy suppliers. After the intervention, we summarized our revelations by revisiting our observations, reactions, judgments, and interventions based on the collected data.

In Essay 3, we conducted design science research (Gregor and Hevner, 2013; Hevner et al., 2004; March and Smith, 1995) by following Peffers et al.'s (2007) six-step process to rigorously develop and evaluate a model. After identifying our research's problem and motivation, we derived the model's objectives (i.e., design requirements) from the literature by relying on Sonnenberg and Vom Brocke's (2012) evaluation criteria for models. We developed and evaluated the model in three phases. In phase 1, we conducted seven design iterations, demonstrated the model by applying it in the manufacturing domain based on a knowledge base gathered from a literature analysis, and evaluated the model's feasibility to fulfill the design requirements with logical arguments based on the illustrative scenario (Peffers et al., 2012). In phase 2, we conducted three design iterations and applied the model to a "real-world situation as part of a research intervention, evaluating its effect on the real-world situation" (i.e., action research) (Peffers et al., 2012, p. 402). In phase 3, we conducted one design iteration, incorporating the insights from 17 semi-structured interviews assessing the practitioners' feedback (expert evaluations) (Peffers et al., 2012).

In Essay 4, we conducted design science research (Gregor and Hevner, 2013; Hevner et al., 2004; March and Smith, 1995) so as to rigorously develop and evaluate a method. We executed an assembly-based process model for situational method engineering to purposefully combine established Text Mining techniques (Brinkkemper, 1996; Henderson-Sellers and Ralyté, 2010; Ralyté et al., 2003). So, we pursued the following steps: First, we set the method engineering goal. Second, we specified the method requirements. Third, we iterated between selecting and assembling method chunks until we reached a complete solution (i.e., all completion conditions met). Besides developing the artifact, we thoroughly evaluated it regarding ease of use, feasibility, and effectiveness. By instantiating our method, we could demonstrate its ease of use and feasibility and could apply it to big data analytics' technology landscape as an exemplary scenario to discuss its effectiveness. To evaluate the method's effectiveness, we compared two method variants' results with each other and human judgment (gained from 10 semi-structured interviews) and discussed face validity.

In Essay 5, we conducted qualitative exploratory research following a five-stage research process. In stage 1, we conducted a multi-perspective literature search following Vom Brocke et al. (2009) and Webster and Watson (2002) to identify, analyze, and structure management challenges of AI applications in healthcare. In stage 2, we iteratively developed the AI Application Management (AIAMA) model. In stage 3, we conducted 11 interviews with domain experts (Myers and Newman, 2007) to (a) evaluate and further refine our model presentation by drawing on feedback from them and (b) discuss managerial recommendations. The experts had either a technical, medical, regulatory, or organizational perspective on deploying and operating AI applications in healthcare. In stage 4, we applied our model to the derived management challenges to draw model-based managerial recommendations by analyzing the challenges' root cause, the point at which they become apparent, the point where they can be solved, and the origin of the required information. In stage 5, we combined the insights from the model application and the analyzed interviews to synthesize the managerial recommendations.

In Essay 6, we conducted design science research (Gregor and Hevner, 2013; Hevner et al., 2004; March and Smith, 1995) to rigorously develop and evaluate a method. We relied on the design science research cycles (i.e., the relevance, design, and rigor cycles), as introduced by Hevner (2007). After clarifying the research paper's relevance (i.e., the relevance cycle), we initiated the method's design by relying on Kermack and McKendrick's (1927) SI model and adapted it in subsequent design cycles. To inform the subsequent design cycles, we derived justificatory knowledge from a structured literature search (i.e., the rigor cycle) (Gregor and Hevner, 2013). To evaluate the method's effectiveness, we instantiated our method and pursued a threefold approach: we calculated the method's results using real-world data and compared these results to human judgment as well as the results of alpha centrality, an established systemic risk measure for IT portfolios (Wolf, 2015).

In summary, this dissertation does not rigidly follow a single philosophical position. The thesis' ontological and epistemological assumptions mainly rely on pragmatism and interpretivism (Goldkuhl, 2012). When reflecting on the research objectives, it becomes evident that guiding organizations in designing and managing AI-enabled IS fulfills essential characteristics of a pragmatist position (Goldkuhl, 2012). The essays' pragmatistic position is also overtly reflected in the choice of research paradigms (i.e., clinical research and design science research) and the engagement with practice (e.g., through interviews or intervention) (Ågerfalk, 2020; Goldkuhl, 2012). However, I also followed interpretivist assumptions when emphasizing the importance of the (socially constructed) organizational context (Walsham, 1993). Nonetheless, some of the essays' results (e.g., effect path model or the Text Mining method) may pave the way for future research following positivistic assumptions (Orlikowski and Baroudi, 1991).

5 Summarizing the Results

I will now summarize the essays' results. The results inform choices in organizational design and digital practices and provide artifacts that can support organizations in designing and managing AI-enabled IS.

5.1 Essay 1: What Got You Here Will (Not) Get You There: Rethinking Organizational Capabilities for Machine Learning

In Essay 1, we provide the capabilities framework for machine learning (CFML) that structures the relevant capabilities to successfully lever the ML lifecycle. The CFML describes capabilities classes within two phases: preparation (i.e., organizational capabilities that affect the ML lifecycle prior to its execution) and realization (i.e., organizational capabilities that directly affect ML lifecycle's execution). We identified seven capabilities classes, subsuming 17 organizational capabilities. Besides identifying and structuring the organizational capabilities relevant for levering ML's potentials, we provide their theoretical anchoring in information processing theory (Galbraith, 1973) and the resource orchestration view (Sirmon et al., 2011). Based on the identified and analyzed capabilities requirements, we discussed the capabilities requirements' specificity. Thus, we answered which of the capabilities requirements are new (to organizations).

We contribute to the literature and to practice in multiple ways: 1) We composed a differentiated set of organizational capabilities requirements to lever ML's potentials. 2) We demonstrated how information processing theory and the resource orchestration view complement each other when discussing organizational capabilities for levering a technology's potentials. 3) We provide a theoretical idea on how a technological hierarchy may explain capabilities requirements.

5.2 Essay 2: The Efficacy of Methodological Guidance for Identifying, Evaluating, and Actualizing Artificial Intelligence's Affordances: Revelations from a Project at EnBW

In Essay 2, we explored real-world effects on methodological guidance's efficacy to identify AI use cases (i.e., identify, evaluate, and actualize AI technologies' affordances). Thus, we examined Hofmann et al.'s (2020b) method by answering the following questions: 1) Is the method efficacious? 2) Why is the method (not) efficacious? 3) How can we make the method more efficacious? We found that explicating AI use cases provides practical decision support for actualizing AI technologies' affordances that integrate into the organizational context. During the project, we identified several factors that affected the method's efficacy. We shed light on the need to balance rigor and pragmatism, knowledge's dominating role, the two-sided integration of the organizational context, and the opportunities and challenges of the project team's interdisciplinarity. After addressing these factors in an advanced method, we could confirm its ability to reduce the complexity of AI technologies' nature as a general-purpose technology. Overall, our results emphasize the need for methodological guidance within the continuum of technology determinism (Smith and Marx, 1994) and social constructivism (Pinch and Bijker, 1984).

We contribute revelations that shed light on how organizations identify and actualize. Our clinical research project provides an impactful intervention in practice and contributes to the academic discourse by advancing Hofmann et al.'s (2020b) method for identifying AI use cases and providing hands-on managerial implications considering the method's efficacy. Further, we contribute by elaborating on the practice of clinical research in IS research.

5.3 Essay 3: Opening the Black Box of Artificial Intelligence's Business Value: Toward an Effect Path Model

In Essay 3, we developed the so-called effect path model, which operationalizes affordance actualization theory by relying on the idea of gradual decomposition (Mueller et al., 2010; Saaty, 1987). The effect path model seeks to structurally deconstruct the creation of AI applications' business value into fine-grained cause-and-effect relationships. By applying the effect path model to AI applications, researchers and practitioners can describe and then analyze where and how they lead to business value. As the model's overarching concept, effect paths bridge the gap between a technological perspective and a business one. Thereby, one can build an effect path by sequentially arranging and connecting nodes to a network. Four sequentially arranged pillars and three effects provide the network's necessary structure by localizing the effect path nodes. Thus, the effect path model's inherent logic guides a user, specifying the effect path's nodes and linking them with edges. Besides introducing the model's design, we thoroughly evaluate the method.

We contribute to the literature by designing and evaluating the effect path model that allows practitioners and researchers to systematically decompose AI applications' paths from data towards business value. In this way, we introduce an operationalization of the affordance actualization theory that translates theoretical assumptions into an analytical framework. Besides demonstrating the model's usefulness, we elaborate on its application.

5.4 Essay 4: Inter-Technology Relationship Networks: Arranging Technologies through Text Mining

In Essay 4, we developed an analytical method that systematically arranges technologies in an analyzable and readable inter-technology relationship network. We introduce inter-technology relationship networks as an ordered sequence of undirected, weighted multigraphs with the edges' weight representing the technological relatedness. These network representations allow one to retrace elapsed patterns of technological change based on self-assembled corpora associated with predefined technologies. Technology-related corpora may comprise, among others, patent documents or academic publications. The method's overarching assumption is that similarity between technology-related corpora quantifies technological relatedness (i.e., the proximity and dependency of technologies). Accordingly, the method relies on established Text Mining techniques such as Doc2Vec (Le and Mikolov, 2014) to measure the similarity between the technology-related corpora (i.e., the proximity and dependency of technologies). The resulting relatedness matrices represent the networks' adjacency matrices. Separated text processing pipelines allow one to jointly incorporate different textual information sources. Besides introducing the method's design, we provide an illustrative demonstration and thorough evaluation of the method.

We contribute to the literature by providing a Text Mining method for technology and innovation management and research. This proposed method closes the addressed research gap by using multiple information sources to retrace the evolution of technological distances between predefinable technologies. Accordingly, we provide a tool for research and practice that allows them to analyze the development of technology landscapes and occurring phenomena and to develop decision support systems such as technology forecasting tools.

5.5 Essay 5: How to Manage Artificial Intelligence Applications in Healthcare: Introducing the AIAMA Model

In Essay 5, we provide three primary results: 1) We introduced 39 management challenges of AI applications in healthcare and structured them into four groups (AI application, contextual restrictions, value creation, and process). 2) We provide the AIAMA model, relying on information processing theory to describe what affects AI application management and how to maintain an AI application's target state. The AIAMA model's constructs allow one to inductively summarize observations from reality into researchable objects and explaining the factors of AI application management (Bhattacherjee, 2012; Cronbach and Meehl, 1955). Thus, the AIAMA model considers the derived management challenges as influencing factors that surround the management sphere. The management sphere depicts the de facto AI application management by interacting with the influencing factors. There are two managerial activity types. a) Factor management cycles (i.e., pipeline and data management, contextual alignment, process management, and value creation management) describe management activities between our influencing factors and the inherent AI application management. b) The integrating management cycle coordinates the factor management cycles and grounds the information. 3) We provide 13 model-based and practice-based managerial recommendations concerning three levels: organization, role, and task.

We contribute to the literature and to practice by deriving and structuring the AI application management challenges in healthcare from the literature, providing the AIAMA model that fosters a managerial understanding, and formulating managerial recommendations guiding organizations in managing AI applications in healthcare. The essay's results are useful for all actors in research and practice associated with deploying and operating an AI application in healthcare.

5.6 Essay 6: How Ill Is Your IT Portfolio? Measuring Criticality in IT Portfolios Using Epidemiology

In Essay 6, we developed and evaluated the so-called *on track* or *in difficulty* (TD) method by applying the SI model (Kermack and McKendrick, 1927), representing a recognized network diffusion model in epidemiology in an ITP context. The TD method quantifies systemic risk in the context of ITP by simulating the damage caused by the failure of individual IT projects or the dependent elements of the IT landscape. Thus, we incorporate indirect interdependencies in ITP to capture cascading effects. The TD method applies the TD model, an adapted SI model, to measure each element's criticality in the ITP based on the extent to which a failure of an element would affect the rest of the ITP and the reaction time (i.e., propagation speed). We instantiated the method using Python by relying on the library Ndlib (Rossetti et al., 2018) and demonstrated its application using real-world ITP data. Based on the instantiation and real-word ITP data, we positively evaluated the TD method by comparing its results against human judgments and alpha centrality, a suitable systemic risk measure in the context of ITPM (Wolf, 2015).

We contributed to the discourse on cascading effects in ITP and practice in three ways: 1) We transferred the SI model from epidemiology to the ITP context. 2) We provide a systemic risk measure for ITP that incorporates the damage and the reaction time (i.e., propagation speed). Thus, the TD method complements the set of available risk measures in ITP. 3) We evaluated systemic risk measures in the context of ITP using real-world data. Practitioners can use the TD method to improve risk management in ITP.

6 Discussion and Conclusion

I will now discuss my results and conclude this thesis. Therefore, I will briefly summarize this thesis' introduction (Section 6.1), present an overview of the thesis' contributions to theory and implications for practice (Section 6.2), reflect on the thesis' overarching limitations (Section 6.3), and close with outlining future research opportunities (Section 6.4).

6.1 Summary

Motivated by organizations' need to sustainably realize business value from AI-enabled IS, the aim of this thesis is to guide organizations in designing and managing AI-enabled IS. I structured my thesis along three research goals: identifying relevant organizational capabilities to lever AI technologies' potentials (RG1), guiding organizations in designing AI-enabled IS (RG2), and guiding organizations in managing AI-enabled IS (RG3). The essays relied on clinical research, design science research, and qualitative explanatory or exploratory research. Rigorously following established and novel research methods, the essays' results inform choices in organizational design and digital practices, and provide artifacts that support organizations in designing and managing AI-enabled IS. By deriving organizational capabilities requirements (RG1), Essay 1 informs the organizational design and digital practices, frames the thesis' results, and sheds light on issues that need (scientific) guidance. Following the CFML classification, RG2 guides organizations to foster preparatory capabilities while RG3 addresses the realization capabilities. Besides informing the organizational design and digital practice by rigorously developed knowledge, this thesis provides several artifacts that scholars and practitioners can use. The introduced artifacts guide organizations in identifying AI use cases (Essay 2), deconstructing the creation of AI applications' business value (Essay 3), assessing the evolution of component technologies (Essay 4), managing AI applications (Essay 5), and measuring system risks (Essay 6).

6.2 Contributions to Theory and Implications for Practice[2]

The essays' results contribute to both theory and practice by answering research questions that researchers have not yet answered and whose answers are relevant for the academic discourse and/or practice.

The essays have contributed to theory in multiple ways: Addressing RG1, Essay 1 demonstrates how information processing theory and the resource orchestration view complement each other when discussing organizational capabilities for levering a technology's potentials. Further, Essay 1 provides a theoretical idea on how a technological hierarchy may explain capabilities requirements. Addressing RG2, Essays 2, 3, and 4 contribute to the academic discourse on identifying, evaluating, and actualizing AI technologies' affordances to guide the business value-enhancing design of AI-enabled IS. These essays sharpen our theoretical understanding of AI technologies' business value-creating and value-capturing paths, which may even be transferable beyond AI's technological boundaries. Accordingly, the essays contribute a comprehensive theoretical understanding that integrates the IT ecosystems view and affordance-actualization theory to describe a seamless business value-creating and value-capturing path, starting with a single technology component and ending in the resulting business value. This theoretical understanding guides the design of AI-enabled IS and lays the foundation for the value-oriented management of AI applications. Addressing RG3, Essays 5 and 6 provide managerial guidance to sustain AI-enabled IS creation and capture of business value (RG3). Essay 5 theorizes on managerial practices, incorporating an inter-organizational perspective and introducing the AIAMA model. Essay 6 introduces an adapted SI model and a new systemic risk measure and therefore a new theoretical perspective on the management of risks in ITP. In sum, my thesis provides novel theoretical perspectives on the identification of value-creating and value-capturing paths, their evaluation, their actualization, and management practices that sustain them. Accordingly, the essays provide theoretical lenses on, above all, the interplay between the technical and social subsystems of AI-enabled IS.

The essays also have implications for (future) research: 1) In Essay 1, we break new ground by analyzing a unique dataset (i.e., interviews from a podcast series). 2) Essay 2

[2] A detailed description of the essays' contributions to theory and implications for practice can be found in the essays' discussion or conclusion sections.

demonstrates how scholars could approach clinical research in the IS context. 3) With the effect path model (Essay 3) and the Text Mining approach (Essay 4), I provide artifacts that scholars can use for theorizing.

Besides the essays' relevance for research, they also have implications for practice. The essays' relevance stems from providing design-oriented or management-oriented knowledge and the development of artifacts following the design science research paradigm. These artifacts include a method for identifying AI use cases (Essay 2), the effect path model to evaluate AI use cases (Essay 3), a Text Mining method to analyze evolutionary patterns in IT ecosystems (Essay 4), the AIAMA model to guide AI application management (Essay 5), and the TD method to measure systemic risks (Essay 6). Owing to the essays' relevance for practice, I featured some of the essays' results in papers that target practitioners (Hofmann et al., 2020a; Urbach et al., 2021) and have used the artifacts in projects with organizations

6.3 Limitations

The essays' results are subject to some limitations. A detailed description of the essays' limitations can be found in the essays' discussion or conclusion sections. Therefore, I will now only briefly introduce the thesis' two overarching limitations.

First, IS research on the adoption and use of AI technologies is still in its infancy. This is not least due to the circumstance that companies are also often just at the beginning of their AI initiatives. Therefore, the little practical experience that organizations have had to date limits IS inquiries. Especially in qualitative interview studies, the results must be taken with a grain of salt. We have taken this into account in all essays to the greatest extent possible. For instance, in Essay 1, we increased our access to the small number of genuine ML experts by relying on interviews from the podcast series *AI in Business* (Faggella, 2020). The reality that many AI applications are still in an experimental pilot or proof-of-concept phase also impedes the evidence-based study of human-computer interaction patterns along the path to creating and capturing business value. However, these limitations are common drawbacks when conducting research on emerging technologies.

Second, most of the essays are limited to an intra-organizational perspective on designing and managing AI-enabled IS. However, I also expect promising future research from an inter-organizational perspective, encompassing the entire (AI) technology value network with its various actors, artifacts, and boundary resources.

Third, some of the artifacts (e.g., the Text Mining method or the TD method) have not yet been evaluated with practice. Although we incorporated feedback from practice, studying the use of the developed artifacts in future research would not only provide a more rigorous evaluation but promise interesting insights. For instance, one could think of integrating the developed Text Mining method into a technology scouting approach that guides organizations in practices relying on the Text Mining method.

6.4 Future Research

The adoption and use of AI are "calling into question our fundamental theories and ideas about organizations and organizing" (Bailey et al., 2019, p. 642). Although this thesis addressed the recent calls for IS inquiry in the AI field (e.g., Berente et al., 2019; Buxmann et al., 2019; Hinz et al., 2019; Rai et al., 2019), there is still much room for future research. However, when theorizing on phenomena of AI technology adoption and use, one should account for the fact that AI technologies' affordances are both extensive and diverse. Taking a look in practice, we recognize that " 'low-hanging fruit' projects have been more successful in many firms and are perhaps more consistent with the current narrow intelligence of AI systems" (Benbya et al., 2020, p. x). Accordingly, in outlining future research opportunities (below), I advocate a deliberate examination of different technology and application contexts.

Future research could benefit from analyzing or anticipating business value-creating and value-capturing paths that stem from (AI) technologies. Scholars may therefore apply the effect path model (c.f. Essay 3) on a micro-level (i.e., elements within the effect path networks) and a macro-level (i.e., the overall effect path network). Considering future AI technologies, I expect to see technological advances that bring new affordances as well as constraints, and therefore new IS research questions. Promising AI technologies are already on the horizon. For instance, deep generative learning models (e.g., generative adversarial networks or variational autoencoders) are multifunctional, going beyond media-effective deepfakes (Hofmann et al., 2021a). As another example, federated learning may overcome the requirement of centralizing data for training ML models, fostering privacy or the performance on edge devices (Kairouz et al., 2019; Li et al., 2020). The latter example demonstrates that business value-oriented research may focus not only on improving performance (e.g., more accuracy), but also on mitigating constraints (e.g., privacy issues). Owing to innovation potentials arising from the combination of technology components beyond the scope of AI technologies, future research may therefore aim to both understand and shape convergence of (digital) technologies. For instance, this will become very relevant in the age of the machine economy (i.e., the integration of and participation by economically autonomous machines) (Urbach et al., 2020). Thereby, AI technologies' capabilities to act autonomously may be of particular interest in technology assemblies. Thus, organizations would benefit from understanding IT ecosystems' evolutionary patterns and guidance in technology scouting practices.

Considering the interplay between AI-enabled IS's technical and social subsystems, I recognized great research opportunities on the future of work. Accordingly, it is necessary to shed light on the use of AI applications as a tool to solve challenges in the social subsystem and the resulting implications for the workforce or organizational roles and structures (Benbya et al., 2020; Coombs et al., 2020; Shrestha et al., 2019). Besides AI technologies' capabilities to outperform humans in certain tasks, it is the "ability to learn and act autonomously [that] makes intelligent technological actors very different from most technologies historically used in organizations" (Bailey et al., 2019, p. 643). In this context, I am enthusiastic about research that elaborates on the human-machine configuration, including associated choices in organizational design (e.g., governance mechanisms, coordination, control). Explanatory approaches are diverse, including human-AI hybrids (Rai et al., 2019), hybrid intelligence (Dellermann et al., 2019), or metahuman systems (Lyytinen et al., 2020). Accordingly, one may ask how "configurations of humans and algorithms evolve as firms adopt [...] AI [...] capabilities." (Grønsund and Aanestad, 2020, p. 1). One may even think about how AI applications may manage the human workforce (Robert et al., 2020).

In conclusion, this thesis took a fused perspective on AI-enabled IS's technical and social subsystem, forming a fruitful basis for future research. This fused perspective offers a new understanding of business value-creating and value-capturing paths as well as their accompanying management. Since AI technologies will not be the last game-changing technology, future research may also seek guidance on managerial, methodological, and operational practices that prepare organizations to constantly adapt to emerging technologies.

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Appendices

Appendix A: Declarations of Co-Authorship and Individual Contributions

In the following, I describe the co-authors' contributions to the essays.[3]

Essay 1: What Got You Here Will (Not) Get You There: Rethinking Organizational Capabilities for Machine Learning

This research paper was co-authored by Christoph Buck, Peter Hofmann, Jan Jöhnk, Nina Brucker, and Kevin C. Desouza. The co-authors contributed as follows:

Christoph Buck (co-author)

Christoph Buck co-developed the research project. He contributed by developing the paper's theoretical foundation and engaging in textual elaboration, especially in the theoretical background and discussion section. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Christoph Buck's co-authorship is reflected in the entire research project.

Peter Hofmann (co-author)

Peter Hofmann initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation, analyzing the interviews, and developing the CFML. Further, he engaged in textual elaboration, especially in the introduction, theoretical background, results, discussion, and conclusion sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Peter Hofmann's co-authorship is reflected in the entire research project.

Jan Jöhnk (co-author)

Jan Jöhnk co-developed the research project. He contributed by analyzing the interviews and developing the CFML. Further, he engaged in textual elaboration, especially in the introduction, research method, results, discussion, and conclusion sections. He also participated in research discussions and provided feedback on the

[3] I submitted signed copies that declare the authors' individual contributions with this thesis.

paper's content and structure. Thus, Jan Jöhnk's co-authorship is reflected in the entire research project.

Nina Brucker (subordinate co-author)

Nina Brucker co-developed the research project. She contributed by transcribing and analyzing the interviews. She engaged in textual elaboration, providing a first draft of the manuscript. Thus, Nina Brucker's co-authorship is reflected in the entire research project.

Kevin C. Desouza (subordinate co-author)

Kevin C. Desouza provided mentorship, participated in research discussions, provided feedback on the paper's content and structure, and engaged in textual elaboration. Thus, Kevin C. Desouza's co-authorship is reflected in the entire research project.

Essay 2: The Efficacy of Methodological Guidance for Identifying, Evaluating, and Actualizing Artificial Intelligence's Affordances: Revelations from a Project at EnBW

This research paper was co-authored by Peter Hofmann, Jan Jöhnk, Dominik Protschky, Christoph Buck, Philipp Stähle, and Nils Urbach. The co-authors contributed as follows:

Peter Hofmann (co-author)

Peter Hofmann initiated and co-developed the research project. He contributed by developing, applying, and adapting the artifact and collecting and analyzing case data. Further, he engaged in textual elaboration, especially in the introduction, relevant work, results, and discussion and conclusion sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Peter Hofmann's co-authorship is reflected in the entire research project.

Jan Jöhnk (co-author)

Jan Jöhnk initiated and co-developed the research project. He contributed by developing the initial artifact, elaborating the approach for clinical research, and analyzing case data. Further, he engaged in textual elaboration, especially in the introduction, research approach, results, and discussion and conclusion sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Jan Jöhnk's co-authorship is reflected in the entire research project.

Dominik Protschky (co-author)

Dominik Protschky initiated and co-developed the research project. He contributed by developing and adapting the artifact. Further, he engaged in textual elaboration, especially in the relevant work and results section. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Dominik Protschky's co-authorship is reflected in the entire research project.

Christoph Buck (subordinate co-author)

Christoph Buck provided mentorship, developed the paper's theoretical foundation, participated in research discussions, provided feedback on the paper's content and structure, and engaged in textual elaboration. He also supervised the artifact's application. Thus, Christoph Buck's co-authorship is reflected in the entire research project.

Philipp Stähle (subordinate co-author)

Philipp Stähle co-developed the research project. He contributed by applying the artifact, observing its efficacy, deriving implications for adapting the artifact, and managing the corporate approval processes for submission. He also provided feedback on the paper's content and structure. Thus, Philipp Stähle's co-authorship is reflected in the entire research project.

Nils Urbach (subordinate co-author)

Nils Urbach supervised the research project and provided mentorship. Further, he participated in research discussions, provided feedback on the paper's content and structure, and engaged in textual elaboration. Thus, Nils Urbach's co-authorship is reflected in the entire research project.

Essay 3: Opening the Black Box of Artificial Intelligence's Business Value: Toward an Effect Path Model

This research paper was co-authored by Christoph Buck, Peter Hofmann, Timon Rückel, Leonie Schoeller, and Nils Urbach. The co-authors contributed as follows:

Christoph Buck (co-author)

Christoph Buck co-initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation and engaging in textual elaboration, especially in the introduction, theoretical foundations, and discussion sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Christoph Buck's co-authorship is reflected in the entire research project.

Peter Hofmann (co-author)

Peter Hofmann co-initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation, developing and evaluating the Effect Path Model, analyzing the expert interviews, and supervising four research projects following an action research approach. He engaged in textual elaboration, especially in the introduction, research method, results, discussion, and conclusion sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Peter Hofmann's co-authorship is reflected in the entire research project.

Timon Rückel (co-author)

Timon Rückel co-developed the research project. He contributed by formulating the literature-based design requirements, analyzing the expert interviews, and evaluating the Effect Path Model. He engaged in textual elaboration, especially in the theoretical foundations and results sections and the Appendix. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Timon Rückel's co-authorship is reflected in the entire research project.

Leonie Schoeller (co-author)

Leonie Schoeller co-developed the research project. She contributed by conducting the literature analysis and developing the Effect Path Model. She engaged in textual elaboration, providing a first draft of the manuscript. She also participated in research discussions and provided feedback on the paper's content and structure. Thus, Leonie Schoeller's co-authorship is reflected in the entire research project.

Nils Urbach (co-author)

Nils Urbach supervised the research project and provided mentorship. Further, he participated in research discussions, provided feedback on the paper's content and structure, and engaged in textual elaboration. Thus, Nils Urbach's co-authorship is reflected in the entire research project.

Essay 4: Inter-Technology Relationship Networks: Arranging Technologies through Text Mining

This research paper was co-authored by Peter Hofmann, Robert Keller, and Nils Urbach. The co-authors contributed as follows:

Peter Hofmann (co-author)

Peter Hofmann contributed to this paper as lead author. He originated the research project by formulating and concretizing an idea to develop a method that arranges technologies in an inter-technology relationship network using Text Mining. Thus, he composed the method engineering goals based on an extensive literature review. In particular, he developed and evaluated the method with regard to existing Text Mining techniques. To evaluate the method, he developed a comprehensive instantiation of it. Based on this instantiation, he generated and interpreted the evaluation results. He also formulated most parts of the paper.

Robert Keller (subordinate co-author)

Robert Keller especially contributed to the project by introducing his methodological knowledge as well as his experience and feedback.

Nils Urbach (subordinate co-author)

Nils Urbach especially contributed to the project by introducing his methodological knowledge as well as his experience and feedback.

Essay 5: How to Manage Artificial Intelligence Applications in Healthcare: Introducing the AIAMA Model

This research paper was co-authored by Peter Hofmann, Luis Lämmermann, and Nils Urbach. The co-authors contributed as follows:

Peter Hofmann (co-author)

Peter Hofmann co-initiated and co-developed the research project. He contributed by developing and evaluating the AI application management model. Further, he engaged in textual elaboration, especially in the introduction, research method, and results sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Peter Hofmann's co-authorship is reflected in the entire research project.

Luis Lämmermann (co-author)

Luis Lämmermann co-initiated and co-developed the research project. He contributed by conducting the literature analysis, developing and evaluating the AI application management model, analyzing the expert interviews, and deriving managerial implications. Further, he engaged in textual elaboration throughout the manuscript. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Luis Lämmermann's co-authorship is reflected in the entire research project.

Nils Urbach (co-author)

Nils Urbach supervised the research project and provided mentorship. Further, he participated in research discussions, provided feedback on the paper's content and structure, and engaged in textual elaboration. Thus, Nils Urbach's co-authorship is reflected in the entire research project.

Essay 6: How Ill Is Your IT Portfolio? Measuring Criticality in IT Portfolios Using Epidemiology

This research paper was co-authored by Florian Guggenmos, Peter Hofmann, and Gilbert Fridgen. The co-authors contributed as follows:

Florian Guggenmos (co-author)

Florian Guggenmos initiated and co-developed the research project. He contributed by conducting the literature analysis and interviews and developing and evaluating the *on track* or *in difficulty* (TD) method. Further, he engaged in most of the textual elaboration. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Florian Guggenmos's co-authorship is reflected in the entire research project.

Peter Hofmann (subordinate co-author)

Peter Hofmann co-developed the research project. He contributed by developing, instantiating, and evaluating the *on track or in difficulty* (TD) method. Further, he engaged in textual elaboration, especially in the introduction, research method, and conclusion sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Peter Hofmann's co-authorship is reflected in the entire research project.

Gilbert Fridgen (subordinate co-author)

Gilbert Fridgen provided mentorship, participated in research discussions, provided feedback on the paper's content and structure, and engaged in textual elaboration. Thus, Gilbert Fridgen's co-authorship is reflected in the entire research project.

Appendix B: Other Publications

Table 3. Overview of Other Publications

Reference	VHB JQ3 ranking	Publication state
Urbach, N., Häckel, B., Hofmann, P., Fabri, L., Ifland, S., Karnebogen, P., Krause, S., Lämmermann, L., Protschky, D., Markgraf, M., Willburger, L., 2021. KI-basierte Services intelligent gestalten – Einführung des KI-Service-Canvas. Projektgruppe Wirtschaftsinformatik des Fraunhofer-Instituts für Angewandte Informationstechnik FIT, Hochschule Augsburg, Universität Bayreuth, Frankfurt University of Applied Sciences, Bayreuth, Germany, et al.	n.a.	Published
Geske, F., Hofmann, P., Lämmermann, L., Schlatt, V., Urbach, N., 2021. Gateways to Artificial Intelligence: Developing a Taxonomy for AI Service Platforms, in: Proceedings of the 29th European Conference on Information Systems (ECIS), Virtual.	B	Accepted
Hofmann, P., Rückel, T., Urbach, N., 2021. Innovating with Artificial Intelligence: Capturing the Constructive Functional Capabilities of Deep Generative Learning, in: Proceedings of the 54th Hawaii International Conference on System Sciences, Online. University of Hawai'i at Manoa, Hamilton Library, Honolulu, HI.	C	Published
Hofmann, P., Stähle, P., Buck, C., Thorwarth, H., 2021. Data-Driven Applications to Foster Absorptive Capacity: A Literature-Based Conceptualization, in: Proceedings of the 54th Hawaii International Conference on System Sciences, Online. University of Hawai'i at Manoa, Hamilton Library, Honolulu, HI.	C	Published
Hofmann, P., Jöhnk, J., Protschky, D., Urbach, N., 2020. Developing Purposeful AI Use Cases: A Structured Method and Its Application in Project Management, in: Proceedings of the 15th International Conference on Wirtschaftsinformatik (WI), Potsdam, Germany.	C	Published
Hofmann, P., Jöhnk, J., Protschky, D., Stähle, P., Urbach, N., Buck, C., 2020. KI-Anwendungsfälle zielgerichtet identifizieren. Wirtschaftsinformatik & Management 12 (3), 184–193. https://doi.org/10.1365/s35764-020-00257-z.	n.a.	Published
Hofmann, P., Samp, C., Urbach, N., 2020. Robotic Process Automation. Electronic Markets 30 (1), 99–106. https://doi.org/10.1007/s12525-019-00365-8.	B	Published
Yilmaz, A., Urbach, N., Hinsen, S., Jöhnk, J., Beisel, P., Weißert, M., Blumenthal, S., Hofmann, P., 2020. AI, Our Assistant and Friend – Challenges and Implications for Human-AI Interaction. Ernst & Young GmbH.	n.a.	Published
Hofmann, P., Oesterle, S., Rust, P., Urbach, N., 2019. Machine Learning Approaches Along the Radiology Value Chain - Rethinking Value Propositions, in: Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm, Sweden; Upsala, Sweden.	B	Published
Jöhnk, J., Hofmann, P., Eymann, T., Urbach, N., 2016. Sicheres IT-Sourcing: Technische Möglichkeiten und Ökonomische Implikationen, in: Möstl, M., Wolff, H.A. (Eds.), Datenschutz in Der Betrieblichen Praxis. Jenaer Wissenschaftliche Verlagsgesellschaft, Jena, Germany, pp. 43–63.	n.a.	Published

What Got You Here Will (Not) Get You There: Rethinking Organizational Capabilities for Machine Learning[4]

Authors

Buck, Christoph; Hofmann, Peter; Jöhnk, Jan; Brucker, Nina; Desouza, Kevin C.

Extended Abstract

Organizations are already creating business value by using machine learning (ML) applications across industries (Agrawal et al., 2018), resulting in competitive pressure on lagging organizations. Organizations need an appropriate resource base to develop, train, and deploy ML applications in a way that enables them to achieve ML applications' expected business value. However, it is unclear whether an organization's established resource base that brought it here (e.g., levering technologies known to the organization) will get it there (i.e., levering ML applications' potential). Lacking or weak capabilities may not only limit business value creation but may even result in value destruction (Canhoto and Clear, 2020). To reduce this uncertainty, organizations must understand the necessary organizational capabilities set for levering ML applications and, if necessary, adapt their resource base (Gupta and George, 2016; Nambisan, 2017; Ritter and Pedersen, 2020). Understanding capabilities requirements is relevant because it removes blind spots for organizations' ML adoption and encourages the sustainable development of a capabilities set. Without knowing how new technological characteristics change organizational capabilities requirements, it is left to chance how organizations succeed in adopting artificial intelligence (AI) technologies (Jöhnk et al., 2021). However, the research has lacked a thorough investigation of relevant capabilities for successfully developing, training, and deploying ML applications. Thus, we ask:

Which capabilities set does an organization need to successfully lever ML?

To answer the research question, we conducted qualitative exploratory research to derive a capabilities framework for ML (CFML) in four steps: In step 1, we collected justificatory knowledge on relevant or associated capabilities. We used the gained

4 At the time of publication of this thesis, this essay is in the review process of a scientific journal. Thus, I provide an extended abstract that covers the essay's content.

knowledge to draft the initial version of our framework, which structures the literature-based insights according to typical organizational layers affected by digital innovations. In steps 2 and 3, we sought to better understand ML's specifics and their implications for capabilities requirements by transcribing and analyzing 54 interviews with ML experts from the podcast series *AI in Business* (Faggella, 2020). In step 2, we conducted categorical coding to extract relevant ML capabilities from the interviews and reworked our initial CFML based on new insights. In step 3, we conducted selective coding based on the adjusted categories and subcategories from the revised framework. The gained insights allowed us to further improve the CFML. In step 4, we substantiated our interview findings with further literature and integrated our findings into established theoretical reasoning (i.e., information processing theory and resource orchestration view).

The CFML structures the relevant capabilities to successfully lever the ML lifecycle in two phases: preparation (i.e., organizational capabilities that affect the ML lifecycle prior to its execution) and realization (i.e., organizational capabilities that directly affect ML lifecycle's execution). The CFML introduces capabilities classes, subsuming organizational capabilities that are theoretically anchored in the information processing theory (Galbraith, 1973) and the resource orchestration view (Sirmon et al., 2011). The paper further discusses the capabilities requirements' specificity.

Keywords: Machine learning, ML, artificial intelligence, AI, capabilities, resources, resource orchestration view, ROV, information processing theory, IPT.

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The Efficacy of Methodological Guidance for Identifying, Evaluating, and Actualizing Artificial Intelligence's Affordances: Revelations from a Project at EnBW[5]

Authors

Hofmann, Peter; Jöhnk, Jan; Protschky, Dominik; Buck, Christoph; Stähle, Philipp; Urbach, Nils

Extended Abstract

As a general-purpose technology (GPT), Artificial Intelligence (AI) offers various affordances for creating business value in organizations (Brynjolfsson and McAfee, 2017; Magistretti et al., 2019). Due to the lack of clarity regarding AI technologies' specific added value, organizations face challenges in identifying, evaluating, and actualizing AI technologies' affordances (Hofmann et al., 2020). AI technologies' affordances do not only provide opportunities but also pressure organizations to appropriately react to AI technologies' supposed potential, even if they do not face an acute problem. Consequently, they seek methodological guidance for identifying organization-specific AI use cases that allow for economic exploitation. For instance, this situation came apparent at EnBW, a large German electric utility company and one of the largest energy suppliers in Europe. Driven by the obscurity regarding AI technologies' specific added value for the business management of wind farms, EnBW aimed to clarify their departmental answer to AI technologies' general potential.

While technology selection approaches are common in practice, they reach their limits when levering the potentials of technologies, such as AI technologies, whose purpose is problem-independent. Researchers have recently developed new methods to identify use cases that – given a technology – seek the fitting problem (e.g., Fridgen et al., 2018; Hofmann et al., 2020; Sturm et al., 2021). However, the research lacks a solid understanding of their efficacies and the factors that influence efficacy. This leads to uncertainties regarding the research results' relevance for practice. Thus, we pursue the following research objective: We seek to investigate methodological guidance's

[5] At the time of publication of this thesis, this essay is in preparation for submission to a scientific journal. Thus, I provide an extended abstract that covers the essay's content.

efficacy to identify, evaluate, and actualize AI technologies' affordances. We approached this objective with the following questions:

1) Is the method efficacious? 2) Why is the method (not) efficacious? 3) How can we make the method more efficacious? (Essay 2)

To answer these questions, we followed a clinical research setting. Specifically, we applied and advanced the method for identifying AI use cases introduced by Hofmann et al. (2020). Since clinical research from IS practice is not yet established, we draw on the parallels to clinical research in the medical domain (Hulley et al., 2013). To report extensive experiences and insights from the method's application in practice, we intervened in organizational practices during a six-month project at EnBW. After the intervention, we summarized our revelations by revisiting our observations, reactions, judgments, and interventions based on the collected data.

We found that explicating AI use cases provides practical decision support for actualizing AI technologies' affordances that integrate into the organizational context. During the project, we identified several factors that affected the method's efficacy. We shed light on the need to balance rigor and pragmatism, knowledge's dominating role, the two-sided integration of the organizational context, and the opportunities and challenges of the project team's interdisciplinarity. After addressing these factors in an advanced method, we could confirm its ability to reduce the complexity of AI technologies' nature as a general-purpose technology.

Keywords: Artificial intelligence, use case identification, methodological guidance, affordance theory, affordance actualization, clinical research.

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Opening the Black Box of Artificial Intelligence's Business Value: Toward an Effect Path Model[6]

Authors

Buck, Christoph; Hofmann, Peter; Rückel, Timon; Leonie Schoeller; Urbach, Nils

Extended Abstract

When preparing for or retrospectively evaluating the goal-oriented realization of AI use cases' potentials, organizations need to reflect on where and how AI generates business value. Thus, organizations need to understand how the actualization of AI technologies' affordances leads to business value. However, when modeling AI applications' business value contributions, organizations face two major challenges: The diversity of technological capacity confronts organizations with diverse possible application scenarios (Brynjolfsson et al., 2017; Frank et al., 2019; Hofmann et al., 2020; Magistretti et al., 2019). Second, organizations need to interweave AI technologies' affordances with their organizational context (Buxmann et al., 2019; Canhoto and Clear, 2020).

The literature has lacked a theoretical and model-based consideration of the actualization of AI technologies' affordances as well as an evaluation of their impacts on business value (Du et al., 2019; Strong et al., 2014). Filling this research gap would help actualize AI technologies' affordances, improving value-based decision-making. To our best knowledge, no model or framework exists that depicts the value-creating and value-capturing path of AI use cases in organizations. To address this research gap, we ask:

How to model AI applications' realization of business value from data?

To answer this research question, we conducted design science research by following Peffers et al.'s (2007) six-step process to rigorously develop and evaluate a model. After identifying our research's problem and motivation, we derived the model's objectives (i.e., design requirements) from the literature by relying on Sonnenberg and Vom Brocke's (2012) evaluation criteria for models. We developed and evaluated the model

[6] At the time of publication of this thesis, this essay is in preparation for submission to a scientific journal. Thus, I provide an extended abstract that covers the essay's content.

in three phases. In phase 1, we conducted seven design iterations, demonstrated the model by applying it in the manufacturing domain based on a knowledge base gathered from a literature analysis, and evaluated the model's feasibility to fulfill the design requirements with logical arguments based on the illustrative scenario (Peffers et al., 2012). In phase 2, we conducted three design iterations and applied the model to a "real-world situation as part of a research intervention, evaluating its effect on the real-world situation" (i.e., action research) (Peffers et al., 2012, p. 402). In phase 3, we conducted one design iteration, incorporating the insights from 17 semi-structured interviews assessing the practitioners' feedback (expert evaluations) (Peffers et al., 2012).

As a key result, the so-called effect path model operationalizes affordance actualization theory by relying on the idea of gradual decomposition (Mueller et al., 2010; Saaty, 1987). The effect path model seeks to structurally deconstruct the creation of AI applications' business value into fine-grained cause-and-effect relationships. By applying the effect path model to AI applications, researchers and practitioners can describe and then analyze where and how they lead to business value. As the model's overarching concept, effect paths bridge the gap between a technological perspective and a business one. Thereby, one can build an effect path by sequentially arranging and connecting nodes to a network. Sequentially arranged pillars and effects provide the network's necessary structure by localizing the effect path nodes. Thus, the effect path model's inherent logic guides a user, specifying the effect path's nodes and linking them with edges.

Keywords: Affordance actualization theory, Artificial intelligence, Business value of IS, Design science research, Strategic use of AI applications.

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Inter-Technology Relationship Networks: Arranging Technologies through Text Mining[7]

Authors

Hofmann, Peter; Keller, Robert; Urbach, Nils

Abstract

Ongoing advances in digital technologies – which enable new products, services, and business models – have fundamentally affected business and society through several waves of digitalization. When analyzing digital technologies, a dynamic system or an ecosystem model that represents interrelated technologies is beneficial owing to the systemic character of digital technologies. Using an assembly-based process model for situational method engineering, and following the design science research paradigm, we develop an analytical method to generate technology-related network data that retraces elapsed patterns of technological change. We consider the technological distances that characterize technologies' proximities and dependencies. We use established Text Mining techniques and draw from technology innovation research as justificatory knowledge. The proposed method processes textual data from different information sources into an analyzable and readable inter-technology relationship network. To evaluate the method, we use exemplary digital technologies from the big data analytics domain as an application scenario.

Keywords: Text mining, network, tech mining, patent mining, method construction.

[7] This essay has been published in:
Hofmann, P., Keller, R., Urbach, N., 2019. Inter-Technology Relationship Networks: Arranging Technologies Through Text Mining. Technological Forecasting and Social Change 143, 202–213. https://doi.org/10.1016/j.techfore.2019.02.009.

How to Manage Artificial Intelligence Applications in Healthcare: Introducing the AIAMA Model[8]

Authors

Hofmann, Peter; Lämmermann, Luis; Urbach, Nils

Extended Abstract

Healthcare is one of the most promising application domains of artificial intelligence (AI), promising concrete opportunities to lever AI technologies (Gilvary et al., 2019; Yu et al., 2018). After years of research, organizations are now starting to capture AI technologies' value creation potentials with market-ready AI applications (Garbuio and Lin, 2019). However, AI applications management is a dynamic process that constantly poses new challenges throughout the organization and calls for new coordination and control mechanisms (Benbya et al., 2019; Faraj et al., 2018). Thus, there is a need to guide AI application management to enable organizations to cope with challenges stemming from deployed AI applications (Ananny and Crawford, 2018; Diakopoulos, 2015). Without understanding the challenges that arise from AI applications' deployment, organizations face the risk of AI applications failing in real-world settings (Higgins and Madai, 2020; Pumplun et al., 2021).

To date, the literature has only described AI application challenges; it has rarely addressed practices that solve the shortcomings in deploying and operating AI applications. Considering the complex healthcare system, which consists of multiple parties and diverse interrelationships, it often remains unclear how healthcare organizations should manage AI applications. Thus, we ask:

How to manage AI applications in healthcare?

To answer the research question, we conducted qualitative exploratory research following a five-stage research process. In stage 1, we conducted a multi-perspective literature search following Vom Brocke et al. (2009) and Webster and Watson (2002) to identify, analyze, and structure management challenges of AI applications in healthcare. In stage 2, we iteratively developed the AI Application Management

[8] At the time of publication of this thesis, this essay is in the review process of a scientific journal. Thus, I provide an extended abstract that covers the essay's content.

(AIAMA) model. In stage 3, we conducted 11 interviews with domain experts (Myers and Newman, 2007) to (a) evaluate and further refine our model presentation by drawing on feedback from them and (b) discuss managerial recommendations. The experts had either a technical, medical, regulatory, or organizational perspective on deploying and operating AI applications in healthcare. In stage 4, we applied our model to the derived management challenges to draw model-based managerial recommendations by analyzing the challenges' root cause, the point at which they become apparent, the point where they can be solved, and the origin of the required information. In stage 5, we combined the insights from the model application and the analyzed interviews to synthesize the managerial recommendations.

The paper provides three primary results: 1) Framework of management challenges of AI applications in healthcare. 2) AIAMA model that describes what affects AI application management and how to maintain an AI application's target state. The AIAMA model considers the derived management challenges as influencing factors that surround the management sphere. The management sphere depicts the de facto AI application management by interacting with the influencing factors. Factor and integrating management cycles describe the managerial activities. 3) Model-based and practice-based managerial recommendations.

Keywords: Artificial intelligence, machine learning, healthcare, AI application, AI deployment, management model.

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How Ill Is Your IT Portfolio? Measuring Criticality in IT Portfolios Using Epidemiology[9]

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Abstract

IT project portfolios, consisting of IT projects, also interact with the entire IT landscape. In case of a failure of only one element, existing dependencies can lead to cascading failures, which can cause high losses. Despite the present effects of systemic risk, research into IT portfolio management lacks suitable methods to quantitatively assess systemic risk. We follow the design science research paradigm to develop and evaluate our *on track* or *in difficulty* (TD) method by applying the SI model, representing a recognized network diffusion model in epidemiology, in an IT portfolio context. We evaluate our method using a real-world dataset. We introduce a criticality measure for diffusion models in IT portfolios and compare the TD method's results and the alpha centrality to human judgment as a benchmark. From our evaluation, we conclude that the TD method outperforms alpha centrality and is a suitable risk measure in IT portfolio management.

Keywords: Systemic risk, cascade failure, IT project portfolio, portfolio management, epidemiology, design science

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