From Strategy to Operations:
Understanding and Managing the Integration of
Artificial Intelligence in Organizations

Dissertation

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“Artificial Intelligence is humanity's reflection in the digital mirror - revealing not just our brilliance and creativity but also challenging us to confront our deepest values and ethics.”

ChatGPT 4.5, 2025

Abstract

Effectively managing the integration of artificial intelligence (AI) is critical for organizations seeking to realize its transformative potential. Despite substantial investments and strategic interest, many AI initiatives fail due to fragmented approaches and underdeveloped management capabilities. Given AI's complexity across application, strategic, and operations levels, organizations must adopt holistic management frameworks tailored to AI's unique characteristics. Without such frameworks, firms risk failing to translate technological promises into sustained business value, highlighting the need for research that supports organizations in systematically navigating the organizational and managerial challenges of AI integration. Therefore, this dissertation seeks to provide insights into AI management by addressing four research goals (RGs).

The first research goal (RG1) aims to support organizations in developing a comprehensive understanding of AI. Essay 1 introduces a dynamic categorization framework that delineates the evolving dimensions of AI, enabling structured organizational interpretation and management. The second research goal (RG2) focuses on guiding organizations in strategically managing AI integration. Essay 2 presents a taxonomy of AI strategies for incumbent firms, reflecting AI's distinctive attributes; essay 3 outlines a method to embed AI governance into existing frameworks to address AI-specific risks; essay 4 proposes an iterative method for identifying context-specific AI use cases aligned with strategic objectives. The third research goal (RG3) addresses AI integration at the application level. Essay 5 develops a multi-agent LLM system that enhances ideation processes by supporting divergent and convergent thinking; essay 6 introduces an architecture for continuous risk monitoring in projects using unstructured data; essay 7 examines the implementation of AI decision support in sports refereeing, highlighting technological, ethical, and human collaboration factors. The fourth research goal (RG4) concerns the operations management of AI. Essay 8 identifies monitoring practices for machine learning applications based on a circular quality management model; essay 9 develops a taxonomy of LLM-based synthetic data generation, offering insights into design options for data-driven AI applications.

Keywords: Artificial Intelligence, Autonomous Agents, Organizational Integration, AI Management, AI Strategy.

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Dominik Protschky

Abbreviations and Initializations

AI	Artificial Intelligence
IS	Information System
ML	Machine Learning
GenAI	Generative AI
IT	Information Technology
RG	Research Goal
SOA	Service-Oriented Architecture
EAM	Enterprise Architecture Management
MLOps	Machine Learning Operations
LLM	Large Language Model
PRM	Project Risk Management
IE	Information Extraction
SLR	Systematic Literature Review
ICIS	International Conference on Information Systems
C2E	Conceptual-to-Empirical
E2C	Empirical-To-Conceptual
DSR	Design Science Research
SME	Situational Method Engineering
ADR	Action Design Research
DSS	Decision-Support System
MLR	Multivocal Literature Review

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Introduction:
From Strategy to Operations:
Understanding and Managing the Integration of Artificial Intelligence in Organizations

Abstract

This cumulative dissertation aims to guide organizations in understanding and effectively managing the integration of artificial intelligence (AI) into their organizations. Comprising nine individual essays, this dissertation is structured around four central research goals. The findings contribute to the field of Information Systems (IS) by illuminating the role of various management levels in facilitating the successful integration of AI within organizational contexts.

In the introduction of this dissertation, Section 2 establishes the necessary theoretical foundation by conceptualizing key constructs, including AI, IS management, and the management of AI. Section 3 articulates and justifies the four research goals that guide this dissertation. Section 4 describes the methodological approaches employed across the essays in detail. Section 5 summarizes the core findings, outlining their scholarly contributions and practical implications. Finally, Section 6 offers a comprehensive summary of the contributions in relation to the research goals, discusses overarching theoretical insights, and reflects on practical relevance. This section concludes with an examination of the dissertation's limitations and proposes directions for future research.

Keywords: Artificial Intelligence, Autonomous Agents, Organizational Integration, AI Management, AI Strategy.

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1 Introduction

As a disruptive innovation, artificial intelligence (AI) is widely acknowledged as one of the most transformative technologies with the capacity to reshape industries and redefine competitive advantages (Davenport and Mahidhar 2018; Li et al. 2021). Hence, AI compels organizations to fundamentally reconsider and potentially transform their existing business models to leverage the business value of AI (Grebe et al. 2023; Li et al. 2021). On the practical side, with the rapid advancement and dynamically evolving landscape of AI technologies, competitive dynamics are evolving swiftly, leading firms to invest significantly in AI integration to secure or expand their competitive advantages (Enholm et al. 2022; Shollo et al. 2022). On the academic side, AI's growing strategic relevance for organizations has stimulated a new wave of scientific research, resulting in a growing number of research papers, special issues, and conference tracks reflecting the increasing importance of the topic in the field of information systems (IS) and management (Papagiannidis et al. 2025).

AI refers broadly to technologies enabling machines to behave intelligently by mimicking cognitive functions traditionally associated with human intelligence (Nilsson 1998; Rai et al. 2019). Contemporary AI, primarily based on machine learning (ML), allows computers to learn directly from data, enabling computers to make decisions without explicit programming (Bishop and Nasrabadi 2006; Goodfellow et al. 2016). Although AI has a long historical background, advances in algorithms, accessible frameworks and libraries, computational capabilities, and the exponential growth of accessible data in the near past have significantly enhanced the practical viability of AI and hence have recently led to increasing integration of AI across a wide range of organizational applications (Choudhary et al. 2023). Moreover, the ever-evolving advances in AI (e.g., in areas such as natural language processing, computer vision, and robotic process automation) continue to expand the scope and potential of AI (Benbya et al. 2021; Berente et al. 2021; Collins et al. 2021).

Building on the novel capabilities of AI and the resulting new opportunities, organizations anticipate significant business value from AI, including increased revenue streams, reduced operational costs, and enhanced business efficiency (Bodendorf 2025; Enholm et al. 2022; Shollo et al. 2022). For example, generative AI (GenAI) alone as a sub-field of AI is projected to contribute between $2.6 trillion and $4.4

trillion annually across various applications, highlighting the immense potential of AI technologies (Chui et al. 2023). In alignment with such estimates, industry reports predict that global spending on AI will exceed $632 billion by 2028 (International Data Corporation 2024). Indeed, strategic interest in AI is also evident in the finding that over 80% of organizations perceive AI as a critical opportunity for securing or achieving competitive advantage (Enholm et al. 2022; Ransbotham et al. 2017). The underlying assumption is that organizations will broadly integrate AI to transform products, services, processes, and business models, thereby realizing substantial business value and therefore competitive advantage (van Giffen and Ludwig 2023).

However, despite considerable expectations and investments, many organizations fail to extract tangible business value from AI (Enholm et al. 2021). Numerous studies indicate a prevalent gap between AI integration and the actual realization of anticipated benefits (Keramidis and Shollo 2025; Shollo et al. 2022; Stohr et al. 2024). A significant proportion of AI projects fail to transition into productive deployment, with reports indicating that less than 26% of organizations achieve their expected business value from AI (Cooper 2024; Mittal et al. 2024). Organizations frequently initiate fragmented and isolated AI projects rather than adopt holistic approaches to manage their AI projects (Fountaine et al. 2019; Shollo et al. 2022). Moreover, the management capabilities necessary to leverage AI holistically remain underdeveloped (Shollo et al. 2022). As a result, the transformative potential of AI is often unrealized (Enholm et al. 2022), and the question arises as to why firms fall short in fully capitalizing AI's business value.

From a managerial perspective, the integration of AI in organizations presents challenges across three distinct management levels. First, at an application level, integrating AI with legacy systems, defining meaningful business use cases, and translating AI outputs into actionable decisions require deep domain knowledge and interdisciplinary coordination (Davenport and Mahidhar 2018; Weber et al. 2023). Furthermore, the evolving nature of human-machine interaction (i.e., shifting from automation toward augmentation) further complicates application design, as organizations must consider how AI complements rather than replaces human capabilities (Raisch and Krakowski 2021). Second, at a strategic level, many organizations initiate AI projects without embedding them in a structured strategic framework, leading to fragmented implementation efforts (Faraj and Leonardi 2022; van Giffen and Ludwig 2023). AI's continually evolving nature introduces uncertainties, reshaping strategic management practices and complicating decision-making processes regarding resource allocation, project scope, and implementation speed (Bharadwaj et al. 2013; Borges et al. 2021). Additionally, challenges around governance and ethics emerge, particularly in high-risk sectors such as healthcare and finance, where unintended consequences can be severe (Birkstedt et al. 2023; Schneider et al. 2023). Third, at an operations level, data-related issues, such as integrating and cleaning diverse datasets to enable meaningful AI applications, often pose significant barriers (Mikalef and Gupta 2021). Furthermore, organizations frequently lack the necessary infrastructure investments to support scalable and maintainable AI deployments, hindering the transition from prototype phases to operational applications (Weber et al. 2023).

Addressing these multifaceted challenges necessitates a comprehensive integration of AI at the application, strategic, and operations levels. Yet, existing research often prioritizes technical or isolated perspectives on AI, with limited focus on the organizational and managerial dimensions critical to realizing AI's business value (Enholm et al. 2022). Practitioners likewise cannot rely solely on prior management experiences, as AI's unique characteristics introduce distinct workflows and development dynamics that differ markedly from traditional information technology (IT) initiatives (Vial et al. 2023). This results in new challenges and obstacles for the integration of AI in organizations, which must be addressed with a nuanced perspective on the management of AI (Ågerfalk et al. 2022; Benbya et al. 2021; Berente et al. 2021). This gap underlines the urgency for a holistic management framework that encompasses organizational structure, strategic preparedness, and operational execution, specifically tailored to AI integration (Fountaine et al. 2019; Jöhnk et al. 2021; Vial et al. 2023; Weber et al. 2023). To close this gap, the overall goal of this research thesis is:

Guide organizations in understanding and managing the integration of artificial intelligence in their organizations.

To achieve the overall goal of the dissertation, I examined in 9 essays how organizations can be enabled to understand and manage the integration of AI on a strategic, application, and operations level. Therefore, essay 1 lays the foundational basis for understanding the term AI and integrating AI in organizations. Essays 2, 3, and 4 provide insights into the strategic level; essays 5, 6, and 7 provide insights into the application level; essays 8 and 9 provide insights into the operations level. Hence, this work contributes both to my cumulative dissertation and to the broader academic discourse. It offers theoretical and practical insights that inform organizations and their managers about management practices (e.g., methods, models, frameworks) to assist them in successfully integrating AI into their organizations at different management levels.

The introduction of my dissertation contains the following structure: In Section 2, I provide the required theoretical background by conceptualizing AI, IS management, and the management of AI. In section 3, I derive and motivate four research goals (RGs). In section 4, I explain in more detail the research designs used in my essays. In Section 5, I provide an overview of the key results, contributions, and implications of my essays. In Section 6, I summarize my results regarding my research goals as well as outline the overarching theoretical contributions and practical implications of my dissertation. I conclude Section 6 with limitations and an overview of fruitful further research opportunities. Following the introduction of my dissertation, I provide the nine essays with relevant supplementary material.

When referring to this dissertation, I use the form “I”; when referring directly to the essays, I use the form “we”, as all essays are based on research papers with co-authors (the authors' specific contributions to each of my essays are listed in Appendix A).

2 Background

2.1 Conceptualizing Artificial Intelligence

AI is not a novel phenomenon per se; rather, it has had a relatively long history. Thereby, the period from *1950 to 1969* marked the genesis of AI as a formal discipline (Benbya et al. 2021; Russell and Norvig 2021). The Dartmouth Conference, often cited as the birthplace of AI, galvanized research interest and funding (Collins et al. 2021; Russell and Norvig 2021). The period from 1*966 to 1973* saw growing skepticism as AI systems failed to scale or adapt to more complex tasks (Benbya et al. 2020). The limitations of early general-purpose reasoning systems such as ELIZA and SHRDLU exposed the gap between demonstration systems and general intelligence (Russell and Norvig 2021). Funding cuts and disillusionment, triggered by unmet expectations and empirical failures, ushered in the first "AI winter" (Collins et al. 2021; Russell and Norvig 2021). In the period from *1969 to 1986,* a resurgence of AI occurred through the development of expert systems (e.g., MYCIN in 1972 for medical diagnosis) - programs that encoded domain-specific knowledge using rule-based logic (Benbya et al. 2020). However, the high cost of knowledge acquisition, brittleness of rule systems, and inability to adapt to new data led to another decline in enthusiasm, contributing to the second AI winter by the late 1980s (Russell and Norvig 2021). The *mid-1980s* onward saw a methodological shift toward statistical approaches (Benbya et al. 2020). The rediscovery of backpropagation in 1986 revitalized interest in neural networks (Russell and Norvig 2021). *Since 2011,* deep learning has emerged as a dominant force following the success of deep neural networks in tasks like vision, speech, and language processing (Russell and Norvig 2021). *Since 2017*, the transformer architecture has revolutionized natural language processing through self-attention mechanisms, enabling parallelization and long-range dependency modeling (Vaswani et al. 2017).

Given the long history of AI and its many periods of progress and setbacks, the question arises as to why AI has gained such extraordinary momentum since the 20th century, and particularly since the 2010s. This resurgence of AI since the 2010s is primarily driven by four interrelated factors: First, algorithmic advances, particularly in deep learning, have significantly improved the performance and versatility of AI systems (Choudhary et al. 2023; Collins et al. 2021). These models, often open-source, have enabled broader experimentation and application (Collins et al. 2021; Lins et al. 2021).

Second, toolkits, frameworks, and libraries containing algorithms, data preparation, analysis functions, etc., offer increasingly simpler access to developing AI applications (Lins et al. 2021). Third, increased computational power, especially through affordable GPUs and AI-optimized hardware, has made large-scale model training feasible (Benbya et al. 2020; Choudhary et al. 2023; Collins et al. 2021). The growth of cloud-based platforms further lowers entry barriers for organizations (Lins et al. 2021). Fourth, the availability of large, high-quality datasets has enhanced AI's learning capabilities, allowing for more accurate and generalizable systems (Benbya et al. 2020; Choudhary et al. 2023). Together, these factors have made AI both practical and strategically valuable across industries in recent years (Choudhary et al. 2023; Shollo et al. 2022). Despite the great momentum, the broader application in the industry, and the long history, there is still no generally accepted definition of AI (Bhatnagar et al. 2018; Collins et al. 2021; Monett and Lewis 2018). However, current paradigm trends in AI gave rise to a set of perspectives on the definition of AI within the field of IS research:

Rational Agents Perspective. Russell and Norvig (2021) provide foundational groundwork by synthesizing numerous AI definitions from preceding decades, categorizing them into four distinct paradigms: thinking humanly, acting humanly, thinking rationally, and acting rationally. Their analysis aimed at conceptual clarity, culminating in their influential intelligent agent model, which defines AI as rational agents capable of perceiving their environments and performing actions to achieve specific objectives optimally (Russell and Norvig 2021). This approach has set the foundation for subsequent AI research, providing a comprehensive framework emphasizing goal-directed rationality.

Cognitive Functions Perspective. The cognitive functions lens emphasizes AI's capability to execute tasks traditionally requiring human cognition, such as perception, reasoning, learning, decision-making, and creativity (Benbya et al. 2021; Rai et al. 2019). Rai et al. (2019) elaborate on human-AI hybrid arrangements within digital platforms, highlighting the nuanced roles AI can play, from substituting to complementing human cognitive functions. Benbya et al. (2021) similarly underscore AI's ability to perform human-like cognitive tasks across diverse organizational functions, marking AI as central to innovation and digital transformation.

Agency Perspective. This perspective treats AI as possessing digital agency, capable of autonomous decision-making and responsibility delegation traditionally reserved for humans (Ågerfalk 2020; Baird and Maruping 2021). Ågerfalk (2020) conceptualizes AI as digital agents actively participating in organizational practices, significantly altering interactions and decision-making dynamics. Baird and Maruping (2021) introduce the delegation framework, emphasizing the shifting balance between human and AI agency, where AI artifacts not only perform tasks but can autonomously assume responsibilities, challenging traditional user-centric views.

Frontier of Computing Perspective. From this perspective, AI is not a static technology but a continuously advancing frontier in computing, characterized by increasing autonomy, learning, and inscrutability (Berente et al. 2021). Berente et al. (2021) describe AI as continually evolving capabilities that tackle increasingly complex decision-making problems, transcending conventional IT systems. This dynamic conceptualization frames AI as the current edge of computational innovation, underscoring continuous shifts in managerial practices and organizational strategies as AI technology evolves.

Building upon these broad conceptualizations of AI, there are different techniques to approach the objectives articulated in AI definitions. ML is such a specific technique and the current primary methodological approach, providing the capability to acquire knowledge and adaptively refine performance through experiential interaction with data (Ågerfalk 2020; LeCun et al. 2015). Hence, ML focuses on developing computational algorithms and statistical models that enable computer systems to progressively improve their performance on a specific task by learning from data, without being explicitly programmed with task-specific instructions (Jordan and Mitchell 2015). In other words, ML is an essential mechanism that powers the adaptability and generalizability of current AI systems, enabling them to handle complex tasks and dynamic environments more effectively.

Although there is currently no unique, commonly accepted definition of AI (Bhatnagar et al. 2018; Collins et al. 2021; Monett and Lewis 2018), for my thesis, I will refer to the following definitional aspects. AI can be conceptually defined as computational systems capable of intelligent behavior, characterized by their ability to perform cognitive tasks traditionally reserved for human intelligence (Nilsson 1998; Rai et al. 2019). Instead of merely executing mechanical functions, AI systems engage in cognitive activities such as perception, reasoning, learning, decision-making, creativity, and adaptive problem-solving (Raisch and Krakowski 2021). These capabilities allow AI to progressively enhance their performance by autonomously learning from interactions with data, without explicit, task-specific programming (Jordan and Mitchell 2015; LeCun et al. 2015). Thereby, AI represents a continuously evolving frontier in computing, driven by technological advancements that expand and redefine its capacity to leverage data for creating business value (Benbya et al. 2021; Berente et al. 2021; Collins et al. 2021). Thus, AI embodies an adaptive technology whose boundaries and practical applications continuously evolve, reflecting ongoing developments in autonomy, adaptability, and cognitive sophistication. As such, AI not only redefines technical possibilities but also continuously transforms organizational strategies, managerial practices, and human-machine interactions.

2.2 Conceptualizing Information Systems Management

The concept of management is multifaceted and has been interpreted from various perspectives in both academic and practical literature (Krcmar 2015). For example, from a decision-making perspective, management is often described as making informed choices that shape organizational trajectories (Simon 1960). From a perspective of responding to change, management can be understood as the creation, adaptation to, and coping with change (Leontiades 1982) or the process of enabling individuals to achieve shared objectives and effectively navigate change (Drucker 2008). However, management entails various core activities, including communication, leadership, coordination, and control, with decision-making serving as a central task (Drucker 2008). According to Laudon (2018), managers are not only responsible for solving existing problems and maintaining operations, but also for driving innovation by leveraging new knowledge and information. Hence, the nature of management decisions varies across different levels from more strategy-related to more operation-related (Berente et al. 2021).

However, as information technologies emerged and matured, the management of IT and IS became increasingly significant (Becker et al. 2009). Historically, IT management focused on the automation and information of business processes (Zuboff 1985). Through automation, IT replaced repetitive and codifiable human tasks, thereby enhancing operational efficiency and minimizing errors (Berente et al. 2021). Simultaneously, IT supported human decision-making through mechanisms such as decision support systems, business intelligence, and data analytics (Berente et al. 2021). Within this context, IT management primarily focused on the effective and efficient deployment of technological resources, emphasizing continuous performance improvement and economic efficiency to optimize operations, control costs, and uphold service quality (Becker et al. 2009).

In recent years, the role of IT and IS within organizations has undergone a profound shift. Rather than serving solely as internal service providers, IT and IS management now occupy a more dynamic position within the value chain by contributing to the creation of products and services for both internal and external customers (Riempp et al. 2008). Currently, this shift is strongly driven by the digital transformation of businesses, which has revealed the deep interdependence between IT/IS and business strategy (Bharadwaj et al. 2013). Changes in organizational rules, strategies, and processes are often inseparable from concurrent changes in IT infrastructure, software, databases, and communication technologies (Bharadwaj et al. 2013; Laudon 2018). Hence, IT/IS management is not a standalone function but must be viewed as deeply embedded within and co-evolving with core business processes (Bharadwaj et al. 2013). The interdependence between business and IT/IS led to a redefinition of the role of IT/IS management into a dual role: balancing between stability and change, i.e., not only focusing on operational excellence but also fostering innovation (Laudon 2018).

From a theory perspective, the socio-technical nature of IT/IS management's dual role is also reflected in different IS theories. For example, a foundational perspective is socio-technical systems theory, which posits that successful IT/IS management requires a joint optimization of both the social (i.e., structure and people) and technical (i.e., technology and task) subsystems of an organization (Bostrom and Heinen 1977; Cherns 1976). Another foundational perspective is work systems theory, which conceptualizes an information system as a configuration of people, processes, technologies, and information, all working together to produce business value (Alter 1999, 2008). It contains the work system amidst strategic orientation, operational infrastructure, and contextual environment, thereby offering a comprehensive view of IT/IS management (Alter 2003, 2008). These theoretical perspectives highlight that the management of IT/IS is inherently multidimensional, involving not only the deployment of technology but also its alignment with organizational goals, structures, and human actors.

Moreover, considering the evolving role and theoretical complexity of IS/IT management, various management models have been developed to guide practice and research. In particular, reference frameworks emerged as a remedy to systematically examine the discipline of strategic IT/IS management, offering structured ways to evaluate and design IT/IS functions (Brown 2004; Riempp et al. 2008; Teo and Ang 2000). For example, a widely recognized model is the reference framework for strategic IT/IS management, which articulates different layers of IT management, from strategic alignment to technological infrastructure (Riempp et al. 2008). This model serves to bridge the gap between high-level strategic goals and low-level technical execution. Another overarching model is the 5-level model of enterprise architecture from business informatics, which encompasses the layers infrastructure, data, people and information systems, business processes, and business model (Gimpel and Röglinger 2017). A more focused model is the IT Performance Measurement Maturity Model, which serves IT managers as an artifact to measure and enhance the status quo of their IT, containing the layers contents, organization, and technology (Becker et al. 2009). Also, the perspective of service-oriented architecture (SOA) is more focused. SOA emphasizes modularity, interoperability, and reusability, embedding services in the traditional IT architectural layers business processes, applications, and infrastructure (Mueller et al. 2010). Another influential model is that of Enterprise Architecture Management (EAM), which views the organization as a socio-technical system (Ahlemann et al. 2012). EAM frameworks typically encompass the layers strategy, organization and processes, information systems, and technology infrastructure, each governed by a set of principles to ensure coherence and adaptability (The Open Group 2022).

For my thesis, I built upon the idea that IT/IS management contains several layers, which exhibit different needs and kinds of management to holistically manage IT/IS systems. In the following section, I will outline in more detail how I transfer this perspective on AI management.

2.3 Conceptualizing Management of Artificial Intelligence

From a strategic IT/IS management perspective, firms must adequately prepare their structures, cultures, and capabilities to harness AI's potential effectively (Coombs et al. 2020; Dwivedi et al. 2021; Jöhnk et al. 2021). Hence, the rise of AI transforms not only the roles of engineers and designers but also fundamentally redefines the expectations placed on managers (Seidel et al. 2018). As AI introduces new capabilities, managerial roles must evolve in response to the continual advances of AI technologies, emphasizing the need not only to adapt technologically but also managerially (Berente et al. 2021). They must understand the technological underpinnings, limitations, and potential impacts of AI systems to ensure they are applied responsibly and effectively (Berente et al. 2021). Organizations that fail to equip their managers with the required capabilities risk misalignment between strategy and technology, underutilization of AI investments, and significant ethical and operational risks (Keding 2021; Papagiannidis et al. 2023).

Overall, AI management is not solely about technical implementation (Lämmermann et al. 2024). At its core, it is a socio-technical practice situated at the intersection of evolving computational capabilities and complex organizational realities (Berente et al. 2021; Lämmermann et al. 2024). Hence, AI management encompasses *"[…] leading, coordinating, and controlling an ever-evolving frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems"* (Berente et al. 2021, p. 1). This includes guiding AI strategy, overseeing development and deployment, and ensuring alignment with organizational goals and societal expectations. Following this definition, managers must mediate between competing demands: innovation and regulation, efficiency and ethics, automation and human judgment, among others (Buxmann et al. 2021). In doing so, they play a pivotal role in shaping not only how AI is used but also its broader implications for organizational identity, culture, and legitimacy (Berente et al. 2021).

The growing importance of AI management has catalyzed a wide range of research streams that attempt to address different challenges of managing AI. Among the most prominent are:

- *AI Capabilities*: Studies in this stream explore how organizations can build and leverage dynamic capabilities to support AI-driven innovation and performance (e.g., Hansen et al. 2024; Höhener 2024; Mikalef and Gupta 2021; Sjödin et al. 2021; Weber et al. 2023).
- *AI Adoption and Readiness*: Studies in this stream examine the organizational conditions, such as technological infrastructure and cultural readiness, that facilitate or hinder AI integration (e.g., Duda et al. 2024; Jöhnk et al. 2021; Laut et al. 2021; Pumplun et al. 2019; Stohr et al. 2024).

- *AI Projects and Machine Learning Operations (MLOps)*: Focused on the project-level and operational dimensions of AI, studies in this stream analyze the lifecycle of AI system development, from prototyping to deployment and maintenance (e.g., Baier et al. 2019; Bodendorf 2025; Kreuzberger et al. 2023; Sturm and van Giffen 2025; Vial et al. 2023.).
- *AI Value Creation*: Studies in this stream seek to understand how AI contributes to competitive advantage and organizational value creation through improved efficiency, decision quality, and customer engagement (e.g., Davenport and Ronanki 2018; Grebe et al. 2023; Hansen et al. 2024; Keramidis and Shollo 2025; Shollo et al. 2022.).
- *Human-AI Interaction*: Addressing the socio-technical interface, studies in this stream emphasize the collaboration between humans and AI systems, highlighting issues such as trust, interpretability, and decision-making dynamics (e.g., Diederich et al. 2022; Faraj et al. 2018; Krakowski et al. 2023; Raees et al. 2024; Sowa and Przegalinska 2025).

Despite the richness of these streams, current research often remains fragmented, with a prevailing emphasis on isolated management factors rather than their integration into a cohesive framework for AI management (Lämmermann et al. 2024). Managers play a central role in AI-related decision-making, as they not only oversee the development and implementation of AI systems but also employ them in strategic decision processes, customer targeting, and the ongoing monitoring and adaptation of organizational practices to effectively integrate AI (Berente et al. 2021). Hence, because of its significant potential and challenges, developing a strategic position to effectively manage AI is an important challenge for organizations (Benbya et al. 2021; Buxmann et al. 2021). Nevertheless, AI management is frequently inadequately understood by organizations (Lämmermann et al. 2024).

Managers need to allocate resources, oversee AI projects, and govern the organizations that are shaping the future (Berente et al. 2021). Thereby, they face various challenges: a host of emerging complex challenges around business strategies, human-AI interfaces, data, privacy, security, ethics, labor, human rights, and national security (Faraj et al. 2018; Kellogg et al. 2020; Rahwan et al. 2019; Russell and Norvig 2021; Stone et al. 2016). While a considerable body of research addresses various aspects of AI management, a critical gap persists in understanding AI management as a coherent, holistic practice from a technical and business perspective. Hence, building on the foundations of IT/IS management (section 2.2) and guided by the need that managers need to prepare for AI, I propose three levels for the conceptualization of AI management: strategic, application, and operations level (see Figure 1):

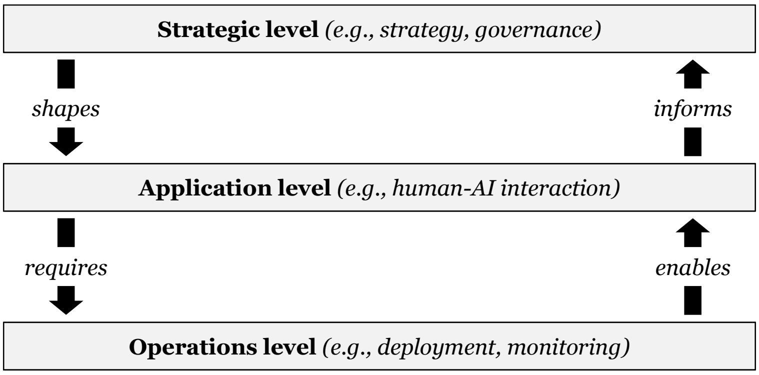

Figure 1. *Three-Level AI Management Model*

This multilevel approach reflects the dual necessity of viewing AI management both as a business-driven strategic imperative and a technically grounded organizational competency. It acknowledges the increasingly complex challenges that AI introduces (Kellogg et al. 2020; Papagiannidis et al. 2025; Vial et al. 2023) and provides a framework for addressing them in an integrated manner.

At a *strategic level*, organizations need to manage the alignment of AI initiatives with business objectives, define long-term vision, and navigate societal implications such as ethics, privacy, and employment (Faraj et al. 2018; Papagiannidis et al. 2025; Rahwan et al. 2019). Here, organizations face the challenges of, for example, mitigating ethical and regulatory risks, managing technological uncertainty, and ensuring adaptive resource allocation amidst rapidly evolving competitive landscapes. At an *application level*, organizations need to manage the design of specific AI applications, ensuring cross-functional collaboration, managing stakeholder expectations, and fostering innovation. Here, organizations face the challenges of, for example, addressing user acceptance and trust, managing domain-specific integration complexities, ensuring effective human-AI collaboration, and mitigating unintended socio-technical impacts of AI solutions. At an *Operations Level*, organizations need to manage the day-to-day functionality, reliability, and compliance of AI applications. Here, organizations face the challenges of, for example, addressing data quality and system scalability issues, continuously monitoring performance and maintaining compliance, and effectively managing ongoing maintenance and updates in dynamic operational environments.

Hence, the strategic level *shapes* the application level by providing foundational perspectives on aspects such as AI strategy, governance, and roadmap development. This foundation ensures that the application level is aligned with organizational goals and strategic priorities. Conversely, the application level *informs* the strategic layer by feeding empirical evidence about human and domain factors back into strategic decision-making. Furthermore, the application level *requires* an effective operational foundation to support the realization of AI's business value in domain-specific contexts. Hence, the application level sets the specific demands for stable, scalable, and context-aware operational systems, ensuring that AI applications are practically executable. Conversely, the operations level *enables* the application level by offering the necessary environments, monitoring frameworks, and preparatory practices that facilitate the effective functioning of AI applications.

3 Research Goals

In this dissertation, I *investigate how to successfully integrate Artificial Intelligence in organizations*. Following my overarching RG (i.e., *guide organizations in understanding and integrating artificial intelligence into their organizations)*, I derive four distinct research goals:

RG1: Guide organizations in understanding the integration of AI

RG2: Guide organizations in managing the integration of AI on a strategic level

RG3: Guide organizations in managing the integration of AI on an application level

RG4: Guide organizations in managing the integration of AI on an operations level

Therefore, the research goals aim to provide the following theoretical and practical insights:

- ***RG1*** aims to investigate how organizations and researchers can approach the concept of AI, as there is currently no commonly accepted definition of AI. The aim is to gain practical and theoretical insights into how to enable a comprehensive understanding of the concept of AI.
- ***RG2*** aims to investigate how the implicitly unique characteristics of AI affect aspects at a strategic level, and to identify the resulting strategic management challenges. The goal is to provide practical and theoretical insights on how to address these challenges in order to manage AI applications successfully at a strategic level.
- ***RG3*** aims to investigate how the implicitly unique characteristics of AI affect the design of AI solutions at the application level, and which particular factors must be considered in this context. The goal is to offer practical and theoretical insights on how to incorporate these relevant factors in order to effectively manage AI solutions at the application level.
- ***RG4*** aims to investigate how the implicitly unique characteristics of AI impact the operations of AI applications at the operations level, and which aspects need to be taken into account. The goal is to provide practical and theoretical insights on how to ensure the successful operations of AI applications, thereby enabling effective management of such systems at an operations level.

Based on my framework (see Sections 2.3), these RGs align seamlessly with the three levels of management. Furthermore, my essays (see Section 5) can be categorized according to these levels, each contributing to the respective level's research goal:

Title	**Publication outlet**	**VHB JQ4 ranking**	**Publication status**
RG1: Guide organizations in understanding the integration of AI			
Essay 1: How to Consider the Artificial Intelligence Term? A Categorization System to Strengthen Research Impact	Scientific Journal	A	In preparation for submission
RG2: Guide organizations in managing the integration of AI on a strategic level			
Essay 2: Conceptualizing the Design Space of Artificial Intelligence Strategy: A Taxonomy and Corresponding Clusters	Business Information Systems Engineering	B	Published
Essay 3: Towards Systematic AI Governance - A Transformation Method	Scientific Journal	B	In preparation for submission
Essay 4: Identifying Artificial Intelligence Use Cases - Towards a Method Facilitating Garbage Can Innovation Processes	Information & Management	B	Published
RG3: Guide organizations in managing the integration of AI on an application level			
Essay 5: Augmenting Divergent and Convergent Thinking in the Ideation Process: An LLM-Based Agent System	European Conference on Information Systems	A	Published
Essay 6: Leveraging Large Language Models for Information Extraction in Project Risk Management	Scientific Journal	B	In preparation for submission
Essay 7: Integrating Artificial Intelligence into Football Refereeing: Insights from German Bundesliga Referees	European Conference on Information Systems	A	Published
RG4: Guide organizations in managing the integration of AI on an operations level			
Essay 8: What Gets Measured Gets Improved: Monitoring Machine Learning Applications in Their Production Environments	IEEE Access	B	Published
Essay 9: Leveraging Large Language Models for the Generation of Synthetic Data	ACM Transactions on Information Systems	B	Submitted

Table 1. *Overview of the 9 Essays, Their Publication Outlets, and Publication Status*

3.1 RG1: Guide organizations in understanding the integration of AI

Essay 1. The AI term, rooted in the ambition to mimic intelligent human behavior through machines, encompasses a diverse set of technologies (Nilsson 1998; Rai et al. 2019). However, over time, this term has come to signify vastly different things to various researchers and practitioners (Grashoff and Recker 2023). From ML and natural language processing to symbolic reasoning, the AI umbrella has grown to cover a broad and often inconsistent array of technologies and methodologies. While this diversity has fueled innovation and research productivity, it has also given rise to conceptual ambiguities that hinder coherent academic progress and real-world applicability (Ågerfalk et al. 2022; Grashoff and Recker 2023).

The core problem addressed in this essay lies in the inconsistent and often vague usage of the term 'Artificial Intelligence.' AI is frequently applied as a general label to a wide array of technologies without clear distinctions or shared characteristics (Collins et al. 2021). This leads to static classification systems becoming obsolete as AI technologies evolve. Hence, one may no longer subsume AI capabilities under the term AI, as they became part of computer capabilities – a phenomenon also known as the 'AI effect' (Stone et al. 2016). Moreover, the indiscriminate use of the AI label results in information loss and a pseudo-accumulation of knowledge, where insights labeled as AI-related may not be genuinely comparable (Collins et al. 2021; Enholm et al. 2022). The lack of definitional clarity impedes cross-disciplinary collaboration and hampers cumulative knowledge building (Ågerfalk 2020; Ågerfalk et al. 2022; Collins et al. 2021; Grashoff and Recker 2023; Mikalef and Gupta 2021; van Giffen et al. 2022).

Numerous efforts have been undertaken to articulate a precise definition of the AI term or to consolidate and synthesize the various definitions that currently exist in literature (e.g., Russell and Norvig 2021). However, existing attempts to define AI either lack the flexibility to accommodate the evolving nature of AI technologies and their socio-technical implications or do not aim to foster cumulative knowledge building. Hence, there is a need for a flexible categorization-based approach to describe AI artifacts and associated activities as combinations of evolving properties rather than fixed types. Such a perspective would support interdisciplinary collaboration and more effective communication between research and practice, and for researchers, it would facilitate more precise theorizing. Thus, we ask:

"How can we categorize and describe AI artifacts together with the associated activities to develop and use these artifacts?"

3.2 RG2: Guide organizations in understanding and managing the integration of AI on a strategic level

Essay 2. AI has rapidly emerged as a transformative force across industries, reshaping how organizations operate, innovate, and compete (Enholm et al. 2022; Grebe et al. 2023; Shollo et al. 2022). With its growing ability to learn autonomously, make decisions, and operate with limited human oversight, contemporary AI differs markedly from traditional IT systems (Ågerfalk et al. 2022; Benbya et al. 2021). This evolution compels organizations to re-evaluate how to design a strategy amidst the unique facets of AI (Buxmann et al. 2021). Hence, to secure or enhance competitiveness through AI, organizations should set up an AI strategy that aligns their AI projects with firm-specific objectives and contextual constraints.

Despite the rising implementation of AI projects in organizations, many organizations struggle to realize their full value due to a lack of appropriate strategic direction (Faraj and Leonardi 2022; Sagodi et al. 2024; van Giffen and Ludwig 2023). This is due to the fact that the unique facets of AI (i.e., autonomy, learning, and inscrutability) (Berente et al. 2021) alter the scale, scope, speed, and sources of existing strategic efforts (Bharadwaj et al. 2013). This means that the unique facets of AI significantly impact market and resource conditions (Rajagopalan and Spreitzer 1997; Ward J. and Peppard J. 2002) as AI-induced market and resource shifts arise. These shifts introduce strategic complexity beyond what traditional IT strategies currently address, meaning there is a need to respond to this strategic complexity in the form of an AI strategy (Keding 2021).

However, academic literature offers only fragmented insights into how organizations should design and implement a comprehensive AI strategy (Collins et al. 2021; Enholm et al. 2022). There is no consolidated understanding of the design space of an AI strategy that organizations can leverage to respond to AI-induced market and resource shifts and their resulting strategic complexity. Hence, this presents challenges for researchers in conceptualizing and analyzing AI strategy design across diverse real-world contexts and for practitioners in identifying key design options for developing or categorizing AI strategies to leverage the full business value of AI. A comprehensive AI strategy serves as the cornerstone for effective AI management at the strategic level, providing a clear framework for subsequent managerial tasks that takes into account the specific characteristics of AI. Thus, we ask:

"What is the design space of an AI strategy in the context of incumbent firms?"

Essay 3. With an AI strategy, AI applications become increasingly embedded in organizational processes, and questions arise about how to effectively govern these applications (Benbya et al. 2021; Wirtz et al. 2022). AI applications differ from traditional IT systems in their ability to learn, adapt, and make autonomous decisions (Baird and Maruping 2021; Berente et al. 2021; Murray et al. 2021), offering significant potential and novel business opportunities (Jöhnk et al. 2021; Shollo et al. 2022). But these inherent characteristics of AI applications also entail various risks and lead to new governance challenges, particularly in relation to ethical concerns surrounding transparency, fairness, and the prevention of discriminatory outcomes (Papagiannidis et al. 2023; Schneider et al. 2023). Hence, with the rise of AI, the concept of AI governance has gained significant attention in research and practice to deal with the complexity and impact of AI technologies, prompting researchers and practitioners to explore new governance frameworks and approaches (e.g., Camilleri 2024; Papagiannidis et al. 2025; Schneider et al. 2023; Wirtz et al. 2022).

Despite a growing body of literature on AI governance, there is still ambiguity about whether existing IT governance frameworks are also sufficient for managing AI's distinct characteristics (Schneider et al. 2023; Wirtz et al. 2022). Some researchers argue that AI demands novel governance mechanisms due to its autonomy and inscrutability (e.g., Papagiannidis et al. 2023), while others argue that established (IT) governance mechanisms can be effectively adapted to meet these emerging demands (e.g., Seppälä et al. 2021). Irrespective of this ambiguity, organizations must, in any case, navigate the complex task of integrating AI technologies in a manner that aligns with risk management protocols, regulatory compliance requirements, and overarching strategic goals, without introducing unnecessary redundancies or fragmenting their governance landscape. Importantly, since not all governance challenges arising from AI are entirely unprecedented, it is both pragmatic and conceptually sound for AI governance research to build cumulatively on the foundational insights provided by IT governance literature.

Nonetheless, there remains a lack of systematic clarity regarding the extent to which AI applications differ from conventional IT in ways that would justify distinct governance mechanisms (Mäntymäki et al. 2022). Although IT governance offers a well-established foundation, current AI governance efforts have only sporadically drawn on this knowledge (Mäntymäki et al. 2022). As organizations increasingly integrate AI, it is essential to clarify how current governance mechanisms and frameworks can be effectively leveraged or adapted to AI-specific governance challenges (Birkstedt et al. 2023). However, a systematic approach to transitioning from IT governance to AI governance remains lacking (Taeihagh 2021), underscoring the need for clearer guidance on aligning existing governance mechanisms with the unique demands of AI technologies. Thus, we ask:

"How can organizations transform their governance framework towards systematic AI governance?"

Essay 4. AI is increasingly becoming integral to organizational transformation, offering vast potential for enhancing innovation, operational efficiency, and competitive positioning (Brynjolfsson and McAffee 2017; Magistretti et al. 2019). One key pathway for realizing AI's potential is through the identification of AI use cases (Brakemeier et al. 2021; Brunnbauer et al. 2021; Hofmann et al. 2020), i.e., specific applications where AI technologies can address business problems or unlock new opportunities (Brakemeier et al. 2021; Hofmann et al. 2020). AI use case identification is therefore crucial for aligning AI's capabilities with strategic goals, setting an AI roadmap to transfer strategic aims into tangible value across various sectors (Grebe et al. 2023).

However, identifying AI use cases is not straightforward; rather, the AI use case identification process is fraught with complexity due to AI's unique characteristics (i.e., autonomy, learning, and inscrutability), which result in a continuously evolving technological frontier (Berente et al. 2021). This leads to three specific complications: (1) technology momentum-triggered choice opportunities, where the rapid advancement of AI forces organizations to act without clear direction; (2) an overwhelming variety of potential applications, creating difficulty in navigating the diversity of possible AI solutions; and (3) non-obvious problem-solution matching, where it is hard for stakeholders to evaluate the applicability and value of AI due to its opaque nature. These complications make the decision-making during AI use case identification particularly challenging, often resulting in missed opportunities or inefficient strategies (Brakemeier et al. 2021; Brunnbauer et al. 2021; Hofmann et al. 2020).

Addressing these complications is essential for organizations to effectively and strategically harness AI technologies' potential (Grebe et al. 2023; Hofmann et al. 2020). To formalize organizational responses to this perceived potential of AI technologies, research introduced methodological guidance for identifying AI use cases (e.g., Brunnbauer et al. 2021; Hofmann et al. 2020; Kirschbaum et al. 2022; Sturm et al. 2021). However, methodological guidance to identify AI use cases alone does not guarantee that the complexity and uncertainty of decision-making around AI use cases in real-world contexts is taken into account (Chen and Adamson 2015; Pietronudo et al. 2022). Given the dynamic and emergent nature of AI, static or linear methods may be ill-suited for effective decision-making in the AI use case identification process (Grebe et al. 2023; Studer et al. 2021). Moreover, there is limited empirical evidence on how these approaches perform in practice, particularly with a focus on decision-making under conditions of organizational change and uncertainty. The development of a structured, context-sensitive method for AI use case identification that can guide decision-making is crucial for AI management on a strategic level, as AI use cases realize the strategic scope of an AI strategy or stimulate the creation of an AI strategy. Thus, we ask:

"How to design a method for efficacious decision-making in AI use case identification?"

3.3 RG3: Guide organizations in understanding and managing the integration of AI on an application level

Essay 5. The integration of GenAI, particularly Large Language Models (LLMs), into organizational tasks and processes marks a significant milestone in the history of AI. LLMs exhibit advanced capabilities in natural language understanding and generation, which empower them to perform a broad range of cognitive tasks such as language translation, summarization, and content creation (Bouschery et al. 2023; Nah et al. 2023). Emerging research highlights the transformative potential of LLMs, suggesting that their usage can lead to significant gains in both creativity and productivity (Hacker et al. 2023; Kanbach et al. 2024). Consequently, LLMs hold considerable promise in domains that demand high levels of intellectual engagement and creative ideation, such as the systematic generation of novel ideas (Bouschery et al. 2023).

The generation of innovative ideas through structured ideation processes represents a critical component of organizational success (Kohli and Melville 2019). Both scientific literature and managerial practice consistently underscore the importance of an organization's ability to sense emerging opportunities and translate them into actionable ideas as a key determinant of sustained competitive advantage (Ali et al. 2020). Within this context, ideation emerges as a foundational phase of the innovation process, characterized by the interplay of divergent thinking (i.e., generating a wide array of novel ideas) and convergent thinking (i.e., selecting and refining the ideas) (Banathy 1996; Griebel et al. 2020; Müller-Wienbergen et al. 2011). However, despite growing enthusiasm around the application of LLMs in ideation (i.e., augmenting divergent and convergent thinking), there is a pressing need to investigate how the domain-specific characteristics of ideation processes must be accounted for to fully leverage the capabilities of LLMs (Bouschery et al. 2023).

While AI technologies have been applied in various innovation-related tasks, such as text mining for trend detection (Wang et al. 2022) or customer requirement analysis (Wu et al. 2022), existing research has largely focused on narrow aspects of ideation, rather than offering holistic support across the entire ideation process. Most tools emphasize data processing rather than the creative reasoning needed in ideation (Bouschery et al. 2023). Consequently, organizations face a gap in actionable design knowledge to effectively leverage the potential of LLMs for supporting creative processes such as the ideation process. Thus, we ask:

How to design an LLM-based agent system that augments the ideation process?

Essay 6. Project Risk Management (PRM) remains a cornerstone of successful project execution, especially in complex and dynamic environments (Testorelli et al. 2022). As contemporary projects become more multifaceted (i.e., marked by intricate structural configurations, dynamic external conditions, high degrees of uncertainty, and intricate socio-political interdependencies), the challenges associated with anticipating and mitigating risks are amplified (Vidal et al. 2011). In such contexts, current PRM approaches often prove inadequate, particularly when confronted with the exponential increase of unstructured PRM data (Cagliano et al. 2015; Rohrbeck et al. 2015). This data frequently contains subtle and early indicators of emerging risks, but identifying these indicators in a timely and efficient manner still poses a significant challenge.

Traditional PRM approaches often rely on structured data and formal reporting mechanisms (Okudan et al. 2021). However, the scarcity of structured project data continues to be a major limitation, as early warning indicators often manifest first, for example, in informal, unstructured communications or documents, resulting in a critical detection gap between the emergence and formal identification of risks (Thamhain 2013). This misalignment highlights the need for more tailored approaches to dynamically capture, interpret, and integrate risk indicators from various unstructured sources. With the rise of LLMs, which are capable of understanding and processing natural language, new opportunities have emerged to improve information extraction (IE) of risk indicators from unstructured PRM data (Yang et al. 2024).

Generally, scientific literature has proposed a range of methodological approaches to harness the potential of LLMs for information extraction from unstructured data. For instance, Dagdelen et al. (2024) demonstrated the effective use of LLMs in extracting structured chemical knowledge from unstructured textual sources, Thirunavukarasu et al. (2023) applied LLMs to automate the extraction of clinical information from documents such as electronic health records and radiology reports, or Matthes et al. (2024) used LLMs to structure information from maintenance logs and industry reports into databases. Despite these promising developments, current IE methodologies remain predominantly static and are typically optimized for narrowly defined, temporally bounded use cases (Dagdelen et al. 2024). Their operational effectiveness is largely limited to synchronous extraction scenarios that are explicitly triggered by user input or predefined tasks (Hu et al. 2024). Consequently, these LLM-based extraction methods fail to accommodate the highly domain-specific factors of risk information that shift throughout a project's lifecycle. Thus, we ask:

How can an LLM-based information extraction system be designed to effectively extract relevant project risk indicators from unstructured data sources?

Essay 7. The increasing integration of AI across various industries has found its way into the realm of professional sports (Barlow and Sriskandaraja 2018). As sports continue to digitize and embrace data-driven technologies, AI has emerged as a transformative tool, capable of enhancing performance analysis, crowd management, and notably decision-making in football refereeing (Dellermann et al. 2019; Errekagorri et al. 2020; Frevel et al. 2022). In football, a sport with massive global popularity and high financial stakes, the accuracy and consistency of referee decisions have direct consequences on match outcomes, club revenues, and public trust (Vögele and Schäfer 2019). Accordingly, the application of AI to support refereeing decisions has garnered interest from both researchers and practitioners, offering a potential pathway to address long-standing challenges in maintaining fairness and precision under intense, high-pressure match conditions.

While human referees continue to show a roughly 14% error rate (Mallo et al. 2012), their decisions remain influenced by cognitive load, physical strain, and contextual pressures like crowd noise or player reputations (Brand et al. 2009; Samuel et al. 2021). Despite the promise of AI in improving decision accuracy and fairness, its integration into football refereeing introduces complex challenges (Ephzibah et al. 2020; Gottschalk et al. 2020). Existing technologies, such as VAR and goal-line technology, have already sparked debates about delays, disruption of game flow, and diminished human authority (Karanasios et al. 2023). AI technologies, although powerful in processing large volumes of data quickly, must be aligned with the dynamic, real-time nature of the sport (Errekagorri et al. 2020). Furthermore, to preserve trust and continuity among stakeholders (e.g., fans and players), AI-based decision support systems must be designed to complement referees' authority (Gottschalk et al. 2020).

Hence, there is a need to holistically embed AI in the referee's decision-making process without compromising the game's integrity or attractiveness. To this end, scientific literature provides valuable insights: On the one hand, recent studies provide insights into the design of effective AI-based decision support systems for referees, with a particular focus on real-time accuracy, system transparency, and a high degree of automation (e.g., Jiang and Bao 2022; Ma and Kabala 2024). On the other hand, recent studies have identified key factors shaping AI-based decision support for referees, highlighting the importance of accuracy, consistency, and a balanced integration of AI and human judgment (e.g., Samuel et al. 2021; Zhekambayeva et al. 2024). While existing research acknowledges the potential of AI to significantly improve refereeing decisions, it also reveals a persistent gap in understanding the dynamics of collaborative systems that integrate the complementary strengths of human factors and AI technologies (Gottschalk et al. 2020). Thus, we ask:

What are the influencing factors in integrating AI-based decision support for football referees?

3.4 RG4: Guide organizations in understanding and managing the integration of AI on an operations level

Essay 8. ML has emerged as a cornerstone technology in the current advancement of AI, increasingly adopted by organizations to transform proofs-of-concept into fully operational, production-ready applications (Ågerfalk 2020; McElheran et al. 2024). These ML applications are embedded into complex environments and are expected to deliver consistent, value-driven outcomes. However, their deployment introduces technical and organizational challenges that stem from the inherent unpredictability of production environments (Jöhnk et al. 2021; Lins et al. 2021). Ensuring the reliable operation of ML applications post-deployment demands systematic monitoring practices that can track their performance, ensure alignment with business goals, and mitigate operational risks (Lins et al. 2021; Nalchigar and Yu 2020).

Implementing comprehensive ML monitoring is challenging, as these systems continuously evolve in both their technological foundations and the external conditions they encounter (Benbya et al. 2021; Berente et al. 2021). Traditional software monitoring techniques fall short when applied to ML systems due to the unique characteristics ML applications face in their production environments (Amershi et al. 2019; Sculley et al. 2014). These characteristics contain data drifts and model decay through changes in the real-world (Brown et al. 2021; Shankar et al. 2024), and entanglement with its environments (Bhaskhar et al. 2024; Saputra et al. 2023). Furthermore, ML metrics and assumptions during the development of ML applications may serve as imperfect proxies for real-world phenomena, leading to gaps between model performance in training versus production environments (Flaounas 2017; Naveed 2023). As a result, organizations struggle to manage the health and efficacy of ML applications, increasing the risk of performance degradation, bias, or compliance failures post-deployment (Amershi et al. 2019; van den Heuvel and Tamburri 2020).

Research on monitoring ML applications is still in its early stages, with limited understanding of key monitoring requirements (Paleyes et al. 2023). Most existing studies focus broadly on the ML lifecycle, yet often address monitoring only marginally or not at all, offering little guidance (Qian et al. 2021; Raj et al. 2021). Although MLOps, introduced by major firms like Microsoft, Amazon, and Google, aim to streamline end-to-end ML workflows (Raj et al. 2021; van den Heuvel and Tamburri 2020), they similarly provide minimal guidance on monitoring. Recent technical studies offer initial insights into monitoring tools and components (e.g., Bhaskhar et al. 2024; Bodor et al. 2023; Naveed 2023; Nogare et al. 2024), yet it remains unclear which monitoring practices are essential for ML applications in production settings. Thus, we ask:

What are relevant practices for monitoring ML applications in their production environments?

Essay 9. In the era of digital transformation, synthetic data has gained increasing prominence as a strategic tool to overcome challenges such as data scarcity, high acquisition costs, and privacy concerns (Fonseca and Bacao 2023). Synthetic data refers to information generated artificially rather than collected from real-world processes (Choenni et al. 2023; Fonseca and Bacao 2023; Rossi et al. 2024). LLMs have recently emerged as powerful enablers of synthetic data generation (Koo et al. 2023; Li et al. 2023). With their ability to generate coherent, context-rich textual data, LLMs offer a scalable and versatile approach to simulate real-world scenarios across domains such as, for example, healthcare, finance, and software testing (Blanco-González et al. 2023; Choenni et al. 2023; Goyal and Mahmoud 2025). Their potential to support tasks like model training and system evaluation positions them as vital tools in modern AI-driven analytics and operations (Mishra et al. 2024).

As a response to the promising potential of LLMs for synthetic data generation, recent research has developed a vast number of technical applications to generate synthetic data for purposes such as data augmentation, rapid prototyping, and direct analysis (Rossi et al. 2024). Such applications span a wide range of domains, including question-answering systems (e.g., Boulesnane and Souilah 2024; Chen et al. 2024), the synthesis of tabular data (e.g., Banday et al. 2024; D. Gao et al. 2024, and the creation of multimedia content through multimodal LLMs (e.g., Mishra et al. 2024; Zhao et al. 2025. Additionally, LLM-generated data have been applied in more specialized areas, such as the simulation of network traffic (e.g., Duan et al. 2024; Kholgh and Kostakos 2023, among others.

Despite the promise of LLM-based synthetic data generation, the landscape of applications remains fragmented and lacks a unified conceptual framework. Existing studies often focus on specific applications or isolated technical innovations, without mapping the broader design space or identifying recurring patterns in practice. The result is a lack of clarity on how to systematically deploy LLMs for synthetic data generation, especially given the variety of tasks, data types, and ethical considerations involved. Without a structured understanding of the design options and associated implications, organizations may struggle to responsibly and effectively utilize LLMs for synthetic data generation in real-world scenarios. Addressing this fragmentation is critical not only for improving synthetic data generation but also to guide organizations in making informed choices about model selection, configuration, evaluation methods, and bias management strategies. Thus, we ask:

What are the potential and currently applied design options for utilizing LLMs to generate synthetic data?

4 Research Designs

This section delineates the research designs I implemented across the nine essays to effectively address the established research objectives and questions as outlined in section 3. Table 2 below provides a concise overview of the research designs employed in each of the essays. This is followed by a more detailed explanation of the respective research methods, including the data collection techniques and analysis procedures used.

Title	Research Design
RG1: Guide organizations in understanding the integration of AI	
How to Consider the Artificial Intelligence Term? A Categorization System to Strengthen Research Impact	*Grounded Theory Approach* • Data Collection via a literature review following Kitchenham & Charters (2007) • Analyzing 282 papers via coding following Gioia et al. (2013) and Okoli (2015) • Development of a categorization system based on 1336 descriptive codes, 64 concepts, and 12 themes
RG2: Guide organizations in managing the integration of AI on a strategic level	
Conceptualizing the Design Space of Artificial Intelligence Strategy: A Taxonomy and Corresponding Clusters	*Taxonomy Development and Cluster Analysis* • Development of a taxonomy and derivation of cluster following Kundisch et al. (2021) • Conduction of 5 iterations based on a literature review, 10 interviews, review of professional literature, and 2 rounds of analyzing real-world objects • Development of a taxonomy (with 15 dimensions and 45 characteristics) and derivation of 4 clusters • Evaluation with 5 interviews and a focus-group discussion
Towards Systematic AI Governance - A Transformation Method	*Design Science Research* • Development of a method following Peffers et al. (2007) and Henderson-Seller and Ralyté (2010) • Derivation of 5 Design Objectives based on literature and 10 interviews • Development of a method with four core steps and 8 substeps • Evaluation via 14 interviews, two focus group discussion, and two practitioner workshops with 30 participants in total
Identifying Artificial Intelligence Use Cases - Towards a Method Facilitating Garbage Can Innovation Processes	*Action Design Research* • Development of a method and design principles following Sein et al. (2011) • Conduction 3 iterations in an alpha and beta cycle • Data Collection from 17 interviews and an intervention at EnBW
RG3: Guide organizations in managing the integration of AI on an application level	

Augmenting Divergent and Convergent Thinking in the Ideation Process: An LLM-Based Agent System	*Design Science Research* • Development of an LLM-based multi-agent system following Peffers et al. (2007) • Derivation of 11 Design Objectives from a literature review following Webster and Watson (2002) • Development of a multi-agent architecture • Evaluation via a prototype instantiation and 10 semi-structured interviews
Leveraging Large Language Models for Information Extraction in Project Risk Management	*Design Science Research* • Development of an LLM-based multi-agent system following Peffers et al. (2007) • Derivation of 5 Design Objectives from a literature review following Webster and Watson (2002) • Development of a four-layer based architecture • Evaluation via a prototype instantiation, four interviews, and a focus group discussion
Integrating Artificial Intelligence into Football Refereeing: Insights from German Bundesliga Referees	*Grounded Theory Approach* • Conduction of 15 semi-structured interviews following Myers & Newman (2007) • Coding the interviews via Gioia method following Gioia et al. (2013) • Development of a framework based on 354 first-order, 12 second-order, and 5 third-order concepts
RG4: Guide organizations in managing the integration of AI on an operations level	
What Gets Measured Gets Improved: Monitoring Machine Learning Applications in their Production Environments	*Mixed-Method Approach* • Data Collection via a multivocal literature review and tool analysis following Garousi et al. (2019) and Ogawa & Malen (1991) • Conduction of 10 interviews following Myers & Newman (2007) • Development of 17 monitoring practices
Leveraging Large Language Models for the Generation of Synthetic Data	*Taxonomy Development and Cluster Analysis* • Development of a taxonomy and derivation of clusters following Nickerson et al. (2013) • Conduction of 3 iterations based on a literature review, interviews and focus group discussion, and one round of analyzing real-world objects • Development of a taxonomy (with 13 dimensions and 35 characteristics) and derivation of 4 clusters

Table 2. *Research Design of the 9 Essays*

In ***Essay 1***, we adopted a systematic literature review (SLR) following Kitchenham and Charters (2007) and Okoli (2015) as our methodological approach. For our analysis, we draw on the proposed coding techniques of Gioia et al. (2013) and Miles et al. (2014). Framed as a theoretical review (Paré et al. 2015), we aim to explore and clarify the conceptual variability associated with the term "Artificial Intelligence" in Information Systems (IS) research. Hence, our methodological approach enables the identification and organization of properties that characterize AI artifacts, as well as the activities associated with their development and use in a categorization system.

The data collection phase involved a comprehensive search of academic literature across three domains: senior IS journals, the International Conference on Information Systems (ICIS), and leading management journals. The selection spanned diverse perspectives to ensure coverage of both technical and social aspects of AI. Using the term "Artificial Intelligence" in titles, abstracts, or keywords, we identified 368 publications. After removing non-relevant items and duplicates, we retained 282 papers as our final sample for analysis.

For the data analysis phase, we employed a structured coding process grounded in the approaches of Gioia et al. (2013) and Miles et al. (2014). In the first coding cycle, we inductively assigned descriptive codes to statements within the introduction sections of the selected papers, resulting in 1366 codes, which we consolidated into 64 first-order concepts. In a second coding cycle, we grouped these 64 first-order concepts into 12 second-order themes. Ultimately, in a third coding cycle, we distilled these into three aggregate dimensions (i.e., AI artifact, subject, and context), forming the foundation of our categorization system.

In ***Essay 2***, we adopted a taxonomy-based research methodology, aligning with the organizational systematics approach (Bozeman and McKelvey 1978). For the development of our taxonomy, we followed the guidelines by Kundisch et al. (2022) and for the derivation of clusters (with the help of the taxonomy), we conducted a quantitative cluster analysis following (Sarstedt and Mooi 2016) (Sarstedt and Mooi 2016). This approach allows for the integration of conceptual and empirical insights, suitable for capturing the emergent and multifaceted nature of AI strategy (Kundisch et al. 2022; Nickerson et al. 2013).

For taxonomy development, we followed the 18 steps outlined in Kundisch et al. (2022). For the steps (1) - (5), we defined the research problem as the nascent understanding of AI strategy and motivated its exploration by targeting incumbent firms. We set out to develop a taxonomy to facilitate both academic and practical comprehension of AI strategy design. The objective was to establish a structured framework for identifying, analyzing, and comparing AI strategies. For the steps (6) – (10) we conducted five iterations to design and develop our taxonomy by combining conceptual-to-empirical (C2E) and empirical-to-conceptual (E2C) approaches. The first iteration (C2E) involved a structured literature review according to Webster and Watson (2002). We identified 31 scientific articles, which we then analyzed in three rounds of coding (i.e., open, axial, and selective coding) (Wolfswinkel et al. 2013) to derive our first taxonomy draft. The second iteration (C2E) integrated insights from ten semi-structured expert interviews (Myers and Newman 2007). We also analyzed the interviews in three coding rounds according to Wolfswinkel et al. (2013) to further develop the taxonomy. In the third iteration (C2E), professional literature was reviewed to validate and refine the dimensions and characteristics derived. Again, we analyzed the literature following Wolfswinkel et al. (2013) to triangulate our previous findings (Flick et al. 2004). In the fourth iteration (E2C), we identified 51 real-world examples from which we sorted one-third into the current taxonomy to derive further insights for the development of the taxonomy. In the fourth iteration (E2C), we sorted the remaining two-thirds of the real-world examples into the taxonomy to come to the conclusion that no further revisions of the taxonomy are required. For the steps (11) – (17), we evaluated our final taxonomy (including 15 dimensions and 45 characteristics) against previously defined ending conditions as well as through interviews and a focus group discussion with academic and industry experts. We finished the process of in Kundisch et al. (2022) with step (18) by documenting the taxonomy.

For the derivation of clusters, we performed a cluster analysis using the classified 51 real-world objects to derive four clusters representing common AI strategy archetypes (Ketchen and Shook 1996; Sarstedt and Mooi 2016). We converted taxonomy attributes into dummy variables and applied hierarchical clustering using Ward's method and Euclidean distance (Ward 1963). The optimal number of clusters was determined via dendrogram and elbow criteria, resulting in four clusters. We validated the clustering through expert-based Q-sorting, achieving strong agreement and supporting the reliability and applicability of the identified strategy patterns (Cohen 1960; Moore and Benbasat 1991; Nahm et al. 2002).

In ***Essay 3***, we adopted a Design Science Research (DSR) methodology, which is particularly suitable for addressing complex organizational challenges by developing innovative artifacts (Gregor and Hevner 2013). The approach facilitates both practical problem-solving and the generation of generalizable knowledge (Gregor and Hevner 2013; Hevner et al. 2004). The core artifact we designed is a method for transforming existing IT governance frameworks into systematic AI governance.

Our methodological process followed the six-phase DSR framework proposed by Peffers et al. (2007). In Phase 1, we conducted an extensive literature review to identify the research gap and justify the problem of AI governance transformation. Phase 2 focused on deriving design objectives based on both academic insights and interview input to delineate the expected features and goals of the artifact. In Phase 3, we designed and developed our method by employing Situational Method Engineering (SME), particularly an assembly-based approach (Ralyté et al. 2019). This allowed us to integrate existing method components from IT and AI governance. During this phase, we iteratively refined our method through expert feedback and continuous validation. In Phase 4, the method was demonstrated in expert interviews and focus group discussions. Phase 5 summarized our evaluation: We utilized the FEDS framework (Venable et al. 2016) and the four evaluation activities suggested by Sonnenberg and vom Brocke (2012) to ensure both ex-ante and ex-post evaluations. This included three rounds of semi-structured interviews with 15 subject matter experts (Myers and Newman 2007), two focus group discussions (Krueger and Casey 2015), and two workshops with 30 industry practitioners. Building on this data, we evaluated our problem statement, design objectives, the construct of our artifact, and the use of our artifact. Finally, in Phase 6, we disseminated our findings via academic publication, contributing both theoretical and practical insights into AI governance transformation.

In ***Essay 4***, we adopted an Action Design Research (ADR) approach as delineated by Sein et al. (2011), which merges the strengths of design science research and action research to develop, evaluate, and refine artifacts within practical organizational contexts. This methodology was selected to develop a method that guides decision-making in AI use case identification amidst the complexity and uncertainty characteristic of such innovation processes.

The ADR process followed four phases. In the first phase (problem formulation), we engaged with a practitioner from EnBW who sought structured support to identify AI use cases for the business management of wind farms. This real-world challenge was abstracted into a broader problem class focused on providing methodological guidance for decision-making in contexts described by the garbage can model of organized anarchy (Cohen et al. 1972). The second phase (building, intervention, and evaluation) comprised three iterations. Initially, we evaluated the existing method by Hofmann et al. (2020) through interviews with five external experts. Subsequently, we conducted twelve further interviews within EnBW to adapt and tailor the method to the organization's specific context. This culminated in an alpha version of the method, which we iteratively tested and refined through direct intervention in EnBW's organizational processes, resulting in the beta version of our method. During the intervention, we collected and analyzed data through interviews, observations, and project documentation. In the third phase (reflection and learning), the entire author team systematically revisited all gathered data, observations, and reactions to articulate key insights as "revelations," which subsequently informed the abstraction of design knowledge. Finally, in the fourth phase (formalization of learning), we derived generalized design principles from the intervention. These principles were structured to enhance the adaptability, relevance, and efficacy of methodological guidance for AI use case identification, thus extending the method's applicability beyond the immediate case context.

In ***Essay 5***, we adopted a DSR methodology (Gregor and Hevner 2013; Hevner et al. 2004) to develop an LLM-based agent system aimed at augmenting divergent and convergent thinking in the ideation process. In particular, we followed the DSR process with six phases as proposed by Peffers et al. (2007), which is specifically applicable for prototype-centered designs (Reinecke and Bernstein 2013).

In Phase 1, we identified a lack of design knowledge on leveraging LLMs in ideation by conducting a comprehensive literature review for our problem statement. In Phase 2, we conducted a structured literature review following Webster and Watson (2002), resulting in a final sample of 15 research papers, which built the basis to derive eleven design objectives. In Phase 3, we designed our artifact (an LLM-based agent system) according to the identified objectives. Phase 4 involved the demonstration and documentation of our artifact in the form of an architectural model as our main research outcome (March and Smith 1995). Phase 5, the evaluation phase, followed the multistage framework by Sonnenberg and vom Brocke (2012). We conducted both ex-ante and ex-post evaluations, including internal reviews, prototype instantiation using Microsoft's AutoGen library, and rigorous testing through two fictive case scenarios. Additionally, we performed semi-structured expert interviews with ten experts from diverse industries to evaluate the system's efficacy, usability, and alignment with design objectives (Myers and Newman 2007). The experts validated the artifact's support for divergent and convergent thinking, while also suggesting improvements such as enhanced evaluation mechanisms and transparency. Finally, in Phase 6, we disseminated our findings by publishing the research.

In ***Essay 6***, we also adopted a DSR approach to develop and evaluate an LLM-based information extraction system specifically designed for PRM (Gregor and Hevner 2013; Hevner et al. 2004). Following Peffers et al. (2007), this methodological approach enabled us to create a novel multi-agent system architecture that systematically extracts and processes unstructured project data to proactively identify risk indicators.

In the first step, a comprehensive literature review was conducted to delineate the problem and establish the theoretical foundation. This involved synthesizing insights from both IE and PRM literature. The second step entailed deriving design objectives through semi-structured expert interviews (Myers and Newman 2007) and the academic sources from step one, ensuring that practical and theoretical considerations guided the artifact's design. The third step focused on developing the artifact (i.e., an architecture integrating LLMs within a multi-agent system). In step four, the artifact was demonstrated and documented via a functional prototype developed using Python, SQLite, and Streamlit. Step five emphasized a rigorous evaluation process based on the framework by Sonnenberg and vom Brocke (2012). It consisted of two ex-ante evaluations (literature-based relevance assessment and expert interviews) and two ex-post evaluations (prototype functionality testing and focus group discussion). These evaluations confirmed the architecture's alignment with our design objectives, technical feasibility (i.e., functionality and utility), as well as the practical efficiency, transparency, and alignment of extracted information with existing PRM applications. Finally, step six involves disseminating our research through publication.

In ***Essay 7***, we adopted a qualitative research approach to explore the integration of AI into football refereeing (Bhattacherjee 2012). This methodological approach enabled a nuanced understanding of the complex, real-time decision-making dynamics between human referees and AI systems in high-stakes sporting environments such as football refereeing.

For data collection, we conducted fifteen semi-structured interviews with sixteen participants, comprising referees from Germany's top football leagues, officials from the German Football Association, and AI experts. The semi-structured format provided us with flexibility to explore emerging themes in depth and obtain nuanced, context-specific insights in the nascent field of AI-support in football refereeing (Christensen et al.

2011). The participants were selected purposively to ensure relevance to the research objective, following the qualitative interview principles of Myers and Newman (2007). For the interviews, we developed an interview guide based on scientific literature from decision-support systems (DSS) in sports (Walters 2011). We primarily asked open-ended questions to facilitate an exploratory dialogue and gain in-depth insights aligned with our research aims (Bhattacherjee 2012; Schultze and Avital 2011). Furthermore, given the nascent implementation of AI systems in football refereeing, we employed hypothetical scenarios allowing participants to reflect on possible benefits and challenges.

For data analysis, we followed an inductive approach using the Gioia method (Gioia et al. 2013) to derive conceptual insights. To this end, we used the MAXQDA software to organize and analyze our collected data. We generated 354 first-order concepts, which were subsequently grouped into second-order themes and aggregate dimensions (i.e., third-order concepts) through three coding rounds (Strauss et al. 1996). To maintain analytical rigor and enhance content validity, we conducted our coding rounds in iterative team workshops.

In ***Essay 8***, we adopted a qualitative mixed-method research approach to systematically integrate scientific and practical insights for identifying relevant monitoring practices for ML applications in production environments (Bhattacherjee 2012; Kreuzberger et al. 2022). Hence, we conducted a multivocal literature review (MLR), an interview study, and an analysis of ML monitoring tools.

First, we performed a MLR, encompassing both academic and grey literature (Garousi et al. 2019; Ogawa and Malen 1991). We adhered to rigorous review procedures recommended by Garousi et al. (2019) and Ogawa and Malen (1991). For academic literature, our review led to a final sample of 25 research papers from IEEE Xplore, ACM Digital Library, and arXiv. For practitioner literature, we reviewed 56 articles hosted on Medium, whereby the appropriate quality of the articles was examined with the quality assessment checklist for secondary literature introduced by Garousi et al. (2019). This phase helped synthesize the current understanding and practical challenges of ML monitoring.

Second, we conducted ten semi-structured interviews with data scientists, ML engineers, and domain experts across multiple industries. Following the guidelines from

Myers and Newman (2007) and Schultze and Avital (2011), the interviews were structured around general ML monitoring challenges as well as technical and organizational monitoring dimensions. The data were analyzed using the coding techniques of Saldaña (2021) and Corbin and Strauss (1990), thereby providing rich empirical insights into real-world ML monitoring practices.

Third, we reviewed 15 ML monitoring tools referenced during the interviews and literature review. Tool documentation and publicly available data were examined using open, axial, and selective coding techniques (Corbin and Strauss 1990; Saldaña 2021). This analysis enabled us to triangulate our findings from the MLR and interviews as well as assess how theoretical and empirical insights are instantiated in actual ML monitoring tools, revealing both best practices and notable gaps in current monitoring implementations.

In ***Essay 9***, we adopted a taxonomy-based methodological approach following the guidelines proposed by Nickerson et al. (2013), which is particularly suited for categorizing and analyzing design options in emerging and complex technological domains. The overarching goal is to systematically explore how LLMs can be leveraged for synthetic data generation across diverse contexts.

Before we started developing the taxonomy, we derived our meta-characteristic from our research question. The taxonomy development was conducted in three iterations, and after each iteration, we evaluated the taxonomy against our objective and subjective end conditions. The first iteration utilized a C2E approach rooted in a structured literature review across major academic databases. We identified 94 relevant publications that formed the theoretical basis for our initial taxonomy. The second iteration also followed a C2E approach, integrating insights from semi-structured expert interviews and a focus group discussion with nine domain experts. In the final iteration, we applied an E2C approach by analyzing 94 real-world software artifacts. This empirical grounding allowed us to validate the taxonomy and finalize it with 13 dimensions and 35 characteristics, as we reached all subjective and objective ending conditions.

To derive archetypes from the finalized taxonomy, we conducted a hierarchical cluster analysis based on 94 real-world examples by following four steps for clustering (Sarstedt and Mooi 2016). First, variables were transformed into binary forms. Second, we chose Ward's method with Euclidean distance for clustering (Ward 1963). Third, we determined the optimal number of clusters through a dendrogram inspection and the elbow criterion, leading to four distinct clusters. Fourth, we subsequently interpreted the clusters as archetypes, representing distinct patterns of LLM usage for synthetic data generation. These archetypes offer a typological lens through which to understand prevailing strategies in the field.

5 Summary of Results

In the following, I summarize the core results and contributions of my essays, which shape the management of AI along the strategic, application, and operations levels.

5.1 Essay 1: How to Consider the Artificial Intelligence Term? A Categorization System to Strengthen Research Impact

To answer our research question “How can we categorize and describe AI artifacts together with the associated activities to develop and use these artifacts?” we conducted a SLR to develop a categorization system that accounts for the diverse and evolving nature of AI artifacts. Our key results include a three-dimensional categorization system composed of (1) AI artifact, (2) subject, and (3) context, offering flexibility and specificity for defining AI research subjects.

Our results reveal a comprehensive categorization framework comprising twelve second-order themes and numerous underlying concepts grouped under three aggregate dimensions. First, the AI artifact dimension includes themes such as underlying technique, appearance, and anticipated benefit, highlighting technical and functional characteristics of AI systems. Second, the subject dimension considers aspects like user perception, conditions, intentions, and the influence of AI usage on individuals and organizations. Third, the context dimension encapsulates the activity perspective (development or usage), affected domain, organizational environment, changes in the division of labor, and task design changes. This categorization system enables researchers to identify and describe which characteristics their AI-related research topics share and differ, thus mitigating the risks of incoherent conceptualizations and facilitating clearer communication of research scope and relevance. To support the use of the categorization system, we also provide a three-step guide and an example application of the categorization system to two research papers using the guide.

The core contributions of our work lie in the provision of a mutable and expandable categorization system that aligns with the family resemblance theory (Wittgenstein et al. 2009), addressing the limitations of traditional classification systems that are not suitable to keep pace with the evolving developments of AI technologies. Hence, the categorization system aids cumulative knowledge building by clarifying definitional ambiguities and enhancing interoperability among interdisciplinary research efforts.

Furthermore, it bridges gaps between isolated research strands and supports more rigorous and reflective empirical work by allowing precise articulation of what constitutes AI in a given study.

5.2 Essay 2: Conceptualizing the Design Space of Artificial Intelligence Strategy: A Taxonomy and Corresponding Clusters

To answer the research question "What is the design space of an AI strategy in the context of incumbent firms?", we adopted a taxonomy-based research method, complemented by a cluster analysis, to identify and categorize the key elements of AI strategies across 51 real-world organizational cases. This led to the development of a taxonomy comprising 15 dimensions and 45 characteristics and the identification of four distinct strategic clusters.

Our results provide a comprehensive view of design options for developing a new AI strategy or evaluating an existing one, structured across four overarching layers: Scope, Scale, Speed, and Source. The *Scope* layer addresses the activities organizations perform within their direct control and ownership, encompassing dimensions such as strategic ownership, organizational anchoring, life cycle management, governance level, control mechanisms, and data governance framework. The *Scale* layer focuses on the leverage effects, such as strategic alliances and partner ecosystems, and includes dimensions like knowledge acquisition and technology sourcing. The *Speed* layer pertains to the time and sequence of product and service releases, featuring use case identification and use case expansion. Finally, the *Source* layer describes the mechanisms through which organizations derive value from AI-related products or services, covering technology aspiration, business model impact, risk tolerance, value creation, and value recipient effect. Each dimension serves as a response to a dominant AI-induced market or resource shift, highlighting the unique strategic considerations posed by AI's facets of autonomy, learning, and inscrutability (Berente et al. 2021). Based on the taxonomy, we derive four clusters that represent distinct strategic configurations: (1) the *Technology Navigator*, emphasizing governance and technical capability; (2) the *Innovation Explorer*, prioritizing experimentation and agility; (3) the *Business Enhancer*, focused on value creation through existing capabilities; and (4) the *Operations Stabilizer*, geared toward efficiency and risk mitigation.

The intricacies of an AI strategy, as revealed by our taxonomy and clusters, highlight three key aspects compared to established strategy concepts (Bharadwaj et al. 2013; Woodard et al. 2013). First, some dimensions and characteristics, while known, are now indispensable for overcoming AI-related strategic challenges (e.g., strategic ownership, organizational anchoring). Second, existing dimensions and characteristics, such as technology sourcing, acquire altered meanings due to AI’s inherent facets. Third, certain dimensions and characteristics have gained unprecedented strategic importance, particularly in the "Speed" layer (e.g., use case identification and expansion due to inherent uncertainty in AI) and "Source" layer (e.g., value recipient effect and risk tolerance due to AI's impact on human capabilities and ethical concerns). These nuances underscore the need for a distinct perspective on AI strategy.

Theoretically, this study contributes by articulating a structured, empirically grounded framework for understanding AI strategy in incumbent firms. It expands the strategy discourse by emphasizing the unique requirements and implications of contemporary AI technologies, especially regarding autonomy, learning, and inscrutability. Practically, the findings offer a decision-making aid for managers seeking to craft or refine their AI strategies. The taxonomy and clusters serve as a benchmarking and analysis tool, guiding firms to align AI initiatives with strategic goals and operational constraints, thereby fostering effective AI integration and organizational competitiveness.

5.3 Essay 3: Towards Systematic AI Governance - A Transformation Method

To answer the research question “How can organizations transform their governance framework towards systematic AI governance?”, we adopted a DSR approach to develop and evaluate a method that facilitates the transformation of existing governance frameworks into ones that effectively incorporate AI governance.

We derived five design objectives that guided the subsequent design of our AI governance transformation method: prescribing a flexible but mandatory set of transformation steps, enabling analysis of current governance structures, identifying gaps between existing and necessary AI governance mechanisms, defining relevant AI-specific factors for governance, and facilitating integration rather than the creation of standalone frameworks. Our proposed method follows a structured process with four overarching steps: (1) defining the entry point (including alignment with AI use cases identification, AI strategy development, and AI roadmap setup) to consider an organization’s current AI-related activities; (2) deriving necessary governance mechanisms (including internal and external requirements analysis, risks evaluation, and comparison with current governance structure) to identify overlaps and necessary adjustments in existing governance mechanisms; (3) overall evaluation of the governance mechanisms derived from step 2 to conduct a quality check, balancing costs and benefits; (4) aligning and integrating the AI governance mechanisms with the organization’s broader governance to continuously monitor AI governance effectiveness and efficiency, potentially leading back to the first step for further adjustment iterations.

During our evaluation activities, the interviewed experts confirmed the urgency and relevance of AI governance, driven by the unique impact of AI compared to other technologies. The initial design objectives were largely affirmed, with minor refinements to ensure comprehensive coverage of IT and other governance areas. Furthermore, the experts validated the method’s practical applicability, highlighted its iterative structure, and its adaptability across industries and AI technologies. Lastly, experts applied the method to simulated use cases in workshops, affirming its usability. Key feedback included the importance of continuously assessing AI-related risks and the recommendation to integrate cost-benefit analysis before governance implementation.

Theoretically, the paper challenges the notion of developing separate AI governance structures by arguing for a cumulative and integrative approach that builds on established IT governance principles (Birkstedt et al. 2023; Mäntymäki et al. 2022). It contributes to the discourse by providing a transformation method that contextualizes AI governance as an evolutionary component of IT governance rather than a novel domain. Practically, the artifact offers actionable guidance for practitioners to integrate AI-specific concerns into their existing governance infrastructure. It serves as a flexible framework applicable across industries and maturity levels, facilitating strategic AI integration while addressing ethical, legal, and operational risks (Papagiannidis et al. 2023; Papagiannidis et al. 2025).

5.4 Essay 4: Identifying Artificial Intelligence Use Cases - Towards a Method Facilitating Garbage Can Innovation Processes

To answer the research question “How to design a method for efficacious decision-making in AI use case identification?”, we adopted an ADR approach to develop, test, and refine a structured method. This method enabled the identification of seven practical AI use cases within EnBW, one of Europe’s largest energy suppliers.

The developed method consists of six activities: *Scoping* and *preparing* activities ensure focus and efficiency by defining project boundaries, potential problem and solution spaces, and relevant organizational context factors. *Discovering* involves identifying problems and solutions from both existing challenges and AI technology-induced opportunities. *Understanding* requires contextualizing these identified problems and solutions within the organizational setting and among relevant participants. *Designing* then facilitates the matching of problems with solutions, forming choice opportunities, and leveraging AI's potential. The final step, concluding, supports the transition from AI use case identification to implementation. The method execution (i.e., intervention) resulted in EnBW identifying seven relevant AI use cases, including improvements to existing processes, alterations to existing processes, and the exploration of new fields.

When reflecting and learning about the method's execution, we gained four important revelations: (1) the necessity of balancing academic rigor with practical pragmatism; (2) the pivotal role of knowledge management throughout the identification process; (3) the mutual influence between method execution and organizational context; and (4) the significance of interdisciplinary team collaboration.

From these revelations, we derived six design principles that help to cope with the AI-specific complications in AI use case identification (i.e., technology momentum-triggered choice opportunities, overwhelming variety, and non-obvious problem solution matching). These principles emphasize the importance of iterative scoping with termination options, demand-oriented method scaling, contextual integration of AI solutions, efficient search strategies, early-stage data experimentation, and the use of a cognitive function lens to bridge comprehension gaps.

The core theoretical contribution of our work lies in applying the garbage can model to AI use case identification as an innovation process, thereby reconceptualizing AI use case identification as an organized anarchy of problems, solutions, participants, and choice opportunities. Practically, our research offers a method that enables organizations to derive valuable, contextually embedded AI use cases.

5.5 Essay 5: Augmenting Divergent and Convergent Thinking in the Ideation Process: An LLM-Based Agent System

To answer the research question “How to design an LLM-based agent system that augments the ideation process?”, we adopted the DSR method to design, instantiate, and evaluate an LLM-based multi-agent system that supports both divergent and convergent thinking in the ideation process.

Initially, we derived eleven design objectives from scientific literature, encompassing requirements such as interoperability, customization, user-friendly interfaces, and integrated feedback mechanisms. These objectives ensure the artifact facilitates dynamic, context-sensitive ideation and accommodates diverse organizational needs (Bouschery et al. 2023; Chiu et al. 2023).

Based on these design objectives, we developed a comprehensive architectural model composed of eleven agents, categorized into a user and an AI agent level. Thereby, the AI agent level houses generalized and specialized AI agents, each powered by an LLM, providing autonomous capabilities. The generalized agents consist of the chat manager agent, which facilitates the interaction between the user and the specialized agents, and the retrieval augmented generation agent, which can access information from external sources. The specialized agents consist of the planner, problem definer, brainstormer, idea developer, evaluator, and reporter agent. These agents are focused on different aspects of the ideation process and autonomously interact within a structured system to guide the user through ideation. This design ensures seamless execution of divergent and convergent thinking phases in ideation by dynamically integrating user feedback and external information.

The evaluation demonstrated the artifact’s efficacy and relevance. The four-stage evaluation involved internal assessments and semi-structured interviews with ten domain experts. Experts affirmed the system’s capabilities in integrating user input, enhancing idea quality, and simulating human-like ideation processes. Suggestions for improvement included expanding analytical capabilities and enhancing the reporting detail.

The core theoretical contributions include the operationalization of the AI-augmented double diamond model of Bouschery et al. (2023). By designing and instantiating an artifact, we translate the theorized potential of LLMs in innovation management into practice, aligning with suggestions from Bouschery et al. (2023) and Griebel et al. (2020). Thereby, our instantiation supports the notion that LLMs can enable the consideration of a greater volume and breadth of ideas. Practically, the artifact serves as a blueprint for organizations to implement LLM-enhanced ideation and improve innovation outcomes through structured and dynamic idea generation.

5.6 Essay 6: Leveraging Large Language Models for Information Extraction in Project Risk Management

To answer the research question "How to design an LLM-based information extraction system to extract relevant project risk indicators?" we adopted a DSR method to develop and evaluate a specialized multi-agent architecture that utilizes LLMs to facilitate proactive and context-aware extraction of risk indicators from diverse unstructured project data.

The design objectives for the LLM-based IE architecture include integration of heterogeneous data sources across project lifecycles, continuous real-time extraction of risk indicators, proactive identification of emerging risks without explicit user initiation, incorporation of implicit expert knowledge, and ensuring reusability of extracted risk data in standardized formats. These objectives were informed by comprehensive literature reviews and expert interviews, emphasizing the necessity for robust integration, continuous monitoring, proactive alerts, and alignment with practical PRM activities.

Our LLM-based IE architecture comprises four layers: Input, Extraction, Storage, and Output. The Input Layer integrates structured and unstructured project-related data, including external databases, internal communications, and recorded meetings. The Extraction Layer employs specialized LLM-driven agents (aggregation, specialized risk, and orchestration agents) to systematically process incoming data, identify nuanced risk indicators, and consolidate findings. The Storage Layer centralizes extracted information and maintains an adaptive prompt repository for consistent improvement. Finally, the Output Layer provides actionable insights through interactive dashboards and proactive notifications, supporting timely managerial decision-making.

The core insights from demonstration and evaluation underline the artifact's capability to effectively bridge detection gaps between informal risk emergence and formal risk identification. The implemented prototype, validated through expert focus groups, demonstrated the architecture's significant effectiveness in extracting and structuring risk indicators, showcasing its potential to substantially improve proactive risk management practices in dynamic and uncertain project environments.

Our results contribute theoretically by extending existing frameworks with a tailored multi-agent LLM-based IE architecture explicitly designed for volatile project contexts, effectively addressing inherent PRM limitations by transforming ambiguous and context-dependent data into actionable insights. Practically, the artifact significantly enhances PRM efficiency through automated extraction and continuous proactive alerting, integrates human expertise effectively, and supports decision-making through intuitive visualization tools. Future research directions suggest addressing scalability, model-specific performance, managing LLM output uncertainties, and integrating robust privacy and compliance measures.

5.7 Essay 7: Integrating Artificial Intelligence into Football Refereeing: Insights from German Bundesliga Referees

To answer the research question "What are the influencing factors in integrating AI-based decision support for football referees?", we adopted qualitative semi-structured interviews with Bundesliga referees and officials to identify five key factors: technical prerequisites, regulation of AI usage, the referee-AI relationship, game impact, and stakeholder acceptance.

Our analysis highlights critical technical prerequisites, emphasizing high-quality data input, seamless workflow integration, and system reliability to enable effective AI decision support. Moreover, regarding the regulation of AI use, standardization and consistency are essential, along with clear regulatory and ethical guidelines to ensure responsible AI deployment in football refereeing. Additionally, the relationship between referees and AI must preserve human authority and effectively delineate decision-making power and referee-AI collaboration, reinforcing referees' confidence without undermining their expertise. Game impact considerations stress the importance of minimal disruptions to the natural game flow, preserving game attractiveness. Lastly, stakeholder acceptance depends critically on fostering trust through transparent communication about AI decision processes, clearly articulated to referees, players, and fans.

Based on the 12 second-order themes within the five aggregated dimensions (i.e., the influencing factors), we derived a framework to highlight the relations between the influencing factors. For all relations between the influencing factors, we point out propositions to stimulate future research. Hence, our study proposes that future investigations focus on exploring technical AI training methods that handle subjective fouls, assess the balance between AI accuracy and game flow disruptions, and further investigate how AI influences referee autonomy and stakeholder acceptance. These propositions outline key directions for expanding understanding of effective AI-human collaboration in sports refereeing.

The core theoretical contributions of this study integrate socio-technical perspectives, identifying comprehensive influencing factors and providing a structured framework that captures the complex interactions between AI technology, refereeing practices, and stakeholder perceptions. Practically, the findings guide the implementation of AI systems in refereeing, advocating a balanced approach to enhance decision accuracy and fairness while retaining the integral human aspects of football officiating. This balanced integration approach aims to support organizational readiness and proactive management of AI adoption challenges, ultimately contributing to fairer, more transparent, and widely accepted referee decisions in professional football.

5.8 Essay 8: What Gets Measured Gets Improved: Monitoring Machine Learning Applications in Their Production Environments

To answer the research question "What are relevant practices for monitoring ML applications in their production environments?", we adopted a qualitative mixed-method research approach combining a multivocal literature review, expert interviews, and tool analysis to identify 17 critical monitoring practices.

The study identified comprehensive practices necessary for monitoring ML applications in their production environments, organized according to a typical quality management cycle: define, measure, assess, act, and control. These practices address unique challenges posed by ML environments such as data representation limitations, metric approximations, implicit assumptions, dynamic real-world changes, and entanglement complexities.

The Define step emphasizes proactively identifying weaknesses of ML applications and compensatory workflows, selecting appropriate metrics across technical and organizational spectrums, and modeling an interconnected metrics system. The Measure step encompasses collecting metadata for context, acquiring ground truth labels when feasible, systematically gathering necessary metrics data, and processing this data for meaningful assessment. The Assess step involves meticulous investigation of collected metrics for data quality issues and detection of various types of drift (concept, data, and virtual drifts). Further, detailed cause-effect analysis is recommended to discern underlying problems and their impacts, emphasizing the importance of analyzing metric deviations. The Act step highlights the critical importance of clearly communicating identified adaptations to stakeholders, employing strategies to enhance interpretability and transparency due to ML applications' inherent complexity. The control step suggests systematic verification of adaptations and iterative improvement in monitoring processes by transferring insights to subsequent monitoring cycles. The overarching cross-sectional monitoring practices underline the necessity of continual iterative learning, proactive mechanisms, and tailored monitoring approaches specific to use cases.

Theoretically, the paper significantly contributes by conceptualizing ML monitoring through the lens of intelligent agent theory, presenting a structured framework for monitoring the dynamic interactions between ML agents and their operational environments. Practically, the results furnish ML engineers and organizational stakeholders with a structured guideline to robustly monitor ML applications, thereby enhancing reliability, accountability, and sustainable value generation from deployed ML systems.

5.9 Essay 9: Leveraging Large Language Models for the Generation of Synthetic Data

To answer the research question "What are the potential and currently applied design options for utilizing LLMs to generate synthetic data?", we adopted a taxonomy-based research method, complemented by a cluster analysis. This approach led to the development of a comprehensive taxonomy comprising 13 dimensions and 35 characteristics across four layers and the identification of four distinct synthetic data generation archetypes.

The taxonomy classifies LLM-based synthetic data generation into four conceptual layers: First, the objective layer captures aspects that describe the need for synthetic data, i.e., the tackled issue with the synthetic data, the task for which the synthetic data is used, and the data space. Second, the transformer-based LLM layer captures aspects that describe the LLM used for synthetic data generation, i.e., model transparency, parameter size, context, fine-tuning, RAG, and prompting. The generation process layer captures aspects that directly affect the generation mechanism, i.e., adaptation frequency and bias management. The output layer captures aspects that characterize the generated synthetic data, i.e., evaluation and type of synthetic data. Hence, the taxonomy offers a structured framework with the relevant dimensions to describe the design options for utilizing LLMs to generate synthetic data.

The cluster analysis revealed four archetypes: The *Practical Open-Source Generalist* relies on medium-sized, open-source models for targeted training purposes. The *High-Capacity Proprietary Specialist* employs large-scale, proprietary models with multi-turn prompting to handle privacy and diversity issues. The *Rapid Deployment Scarcity Solver* prioritizes quick, static deployments using proprietary models to address urgent data shortages. Finally, the *Context-Enriched Structured Data Expert* emphasizes structured tabular outputs, dynamic context, and external retrieval to support rigorous quality and bias management. Hence, these four archetypes characterize the currently most commonly used approaches and the design options used to generate synthetic data with LLMs.

Third, the core theoretical contribution lies in offering a unified conceptual foundation that integrates fragmented LLM practices into a cohesive framework. This enables scholars to systematically investigate synthetic data configurations and expand the understanding of LLM potential. Practically, the taxonomy and archetypes guide practitioners in selecting appropriate LLM configurations based on specific needs such as scalability, ethical considerations, or domain specificity.

6 Discussion and Conclusion

To conclude the introduction of my dissertation, I engage in a critical discussion on the findings presented in the essays. I start this section by providing a comprehensive summary of all key results, through which I highlight the theoretical contributions of the dissertation and derive practical implications. Building on this foundation, I then reflect on the limitations of the dissertation and identify promising avenues for future research. Based on my management framework from the background section, my essays contribute to research and practice at the following levels (Figure 2):

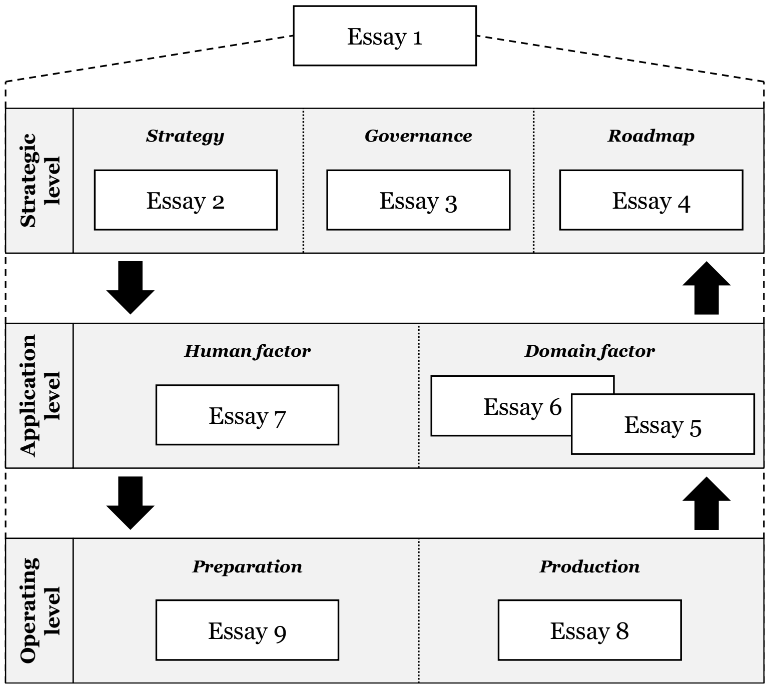

Figure 2. *Essays in the Three-Level AI Management Model*

6.1 Summary

My dissertation addresses the overarching goal of guiding organizations in understanding and managing the integration of AI in their organizations. To this end, my first research goal (RG1) focuses specifically on guiding organizations toward a comprehensive understanding of AI. Hence, essay 1 conceptualizes a categorization framework that accounts for the continuously evolving nature of AI technologies, highlighting various relevant factors encompassed by the concept of AI. Consequently, essay 1 establishes an overarching framework, thereby enabling organizations to manage the integration of AI at the following different levels.

First, I aim to guide organizations in managing the integration of AI on a strategic level (RG2). To this end, essay 2 conceptualizes AI strategy through a comprehensive taxonomy identifying dimensions and clusters of AI strategies for incumbent firms, emphasizing AI’S unique characteristics. These insights provide strategic clarity, helping organizations address specific AI-induced challenges to strategically manage AI applications. Essay 3 develops a systematic method to integrate AI governance into existing governance frameworks, highlighting necessary adjustments and iterative enhancements to manage AI-specific risks effectively. This transformation method supports organizations in strategically managing AI by ensuring governance structures are appropriately tailored to AI's unique characteristics. Essay 4 proposes a structured method to effectively identify AI use cases by leveraging the garbage can model, emphasizing iterative learning, practical applicability, and context-specific solutions. This method equips organizations with a tool to strategically manage the integration of AI use cases in line with firm-specific ambitions and restrictions.

Second, I aim to guide organizations in managing the integration of AI on an application level (RG3). To this end, essay 5 introduces an LLM-based multi-agent system designed to augment divergent and convergent thinking during ideation processes, demonstrating enhanced innovation outcomes. This AI-based artifact offers theoretical and practical insights into effectively incorporating the domain-specific characteristics of ideation processes at the application level, thereby improving ideation quality and productivity. Essay 6 presents an LLM-based multi-agent architecture tailored for proactive extraction and management of project risk indicators from unstructured data. This architecture provides theoretical and practical guidelines for managing AI applications by integrating continuous, context-aware risk monitoring capabilities, thus addressing unique domain factors associated with dynamic project environments. Essay 7 explores influencing factors critical to integrating AI-based decision support systems for football referees, emphasizing technical prerequisites, ethical regulations, and human-AI collaboration. The insights guide practical application management by highlighting essential human factors for successful AI integration in high-stakes contexts like sports refereeing.

Third, I aim to guide organizations in managing the integration of AI on an operations level (RG4). To this end, essay 8 identifies comprehensive monitoring practices necessary for managing ML applications in production, structured around a circular quality management approach. These practices facilitate effective operations management by addressing specific complexities such as drift detection and iterative performance enhancements, ensuring robust and reliable operation of AI systems. Essay 9 develops a comprehensive taxonomy and derives clusters on how to utilize LLMs for synthetic data generation. Hence, the taxonomy reveals insights into the potential design options, and the clusters derived disclose the currently used design options of LLMs for synthetic data generation, facilitating operation management of data for AI applications.

6.2 Theoretical Contributions regarding the Research Goals

Each essay offers different theoretical contributions, which are also presented in detail in my individual essays. Beyond that, they also contribute to the four research goals of my dissertation.

First, essay 1 contributes to the theoretical understanding of AI in the IS domain by developing a categorization system that reflects the diverse socio-technical perspectives on AI. The extendable property structure of the categorization system facilitates a more structured and cumulative knowledge development, thereby mitigating knowledge fragmentation within the research community. Hence, this essay advances a comprehensive understanding of AI by addressing its conceptual ambiguity and promoting coherence across research perspectives. In alignment with the research goal, it offers theoretical foundations and an integrative framework that support researchers in systematically engaging with the multifaceted concept of AI.

Essay 2 contributes to theory by developing a taxonomy that consolidates fragmented knowledge on AI strategy, thereby enabling a shared understanding of its design dimensions and advancing conceptual clarity. Moreover, it establishes a foundational theory for analyzing AI strategy and fosters integration between the information systems and strategic management domains in the context of AI. Essay 3 challenges the prevailing notion of standalone AI governance by proposing an integrative approach that embeds AI governance within existing organizational governance structures. It introduces a transformation method that conceptualizes AI governance as an evolving extension of IT governance, thus offering a novel theoretical lens on the governance of AI. Essay 4 reconceptualizes AI use case identification as a garbage can innovation process, emphasizing the complexity and fluidity of decision-making in this domain. It advances theoretical understanding by offering a method and design principles that capture the unique decision-making challenges posed by AI, grounded in empirical insights from organizational practice. Collectively, the essays 2, 3, and 4 advance the theoretical understanding of how the distinct characteristics of AI shape strategic-level phenomena by elucidating the foundations of AI strategy, redefining governance approaches, and illuminating the dynamics of AI-related decision-making. Together, they offer an integrated theoretical framework for addressing the strategic management challenges of AI, thereby fulfilling the research goal of enabling organizations to strategically manage AI applications more effectively.

Essay 5 advances theoretical understanding at the intersection of AI and innovation management by conceptualizing the interplay between human and computational creativity and demonstrating how LLM-based artifacts can augment ideation processes. It also contributes to DSR by introducing a novel artifact that entangles LLM-driven insights with human ideation, thereby expanding design knowledge for such innovation support systems. Essay 6 extends existing theoretical models in PRM by designing an LLM-based architecture capable of extracting risk signals from unstructured, context-specific communication data. It further contributes by detailing the functioning of a multi-agent system that enables collaborative risk identification through specialized extraction and orchestration mechanisms. Essay 7 enriches the theoretical discourse on AI-supported decision-making in sports refereeing by adopting a socio-technical perspective that incorporates both technological and contextual human factors. It introduces a framework that delineates five interrelated influencing factors, thereby offering a structured basis for understanding the effectiveness and acceptance of AI-assisted refereeing decisions. Collectively, the essays contribute to a deeper theoretical understanding of how AI's unique characteristics shape the design and application of AI solutions across diverse domains. By addressing creativity augmentation, contextual information extraction, and socio-technical integration, the dissertation identifies critical domain factors and interaction mechanisms (i.e., human factors) that inform the effective management of AI at the application level.

Essay 8 advances the theoretical discourse on AI operations by identifying five distinctive characteristics of ML production environments and introducing a conceptual framework that explicates their implications for operational use. Furthermore, it enriches the understanding of operational AI system management by delineating 17 ML monitoring practices and explicating how the identified environment characteristics shape and influence these practices. Essay 9 enriches the theoretical understanding by consolidating the fragmented landscape of LLM-based solutions for synthetic data generation. Moreover, this essay provides a theoretical understanding of the design options of the LLM-based synthetic data generation through a taxonomy and archetypes, thereby fostering and enhancing conceptual understanding. Collectively, the essays 8 and 9 contribute to theory by elucidating how the distinct operational characteristics of AI applications necessitate novel frameworks, practices, and perspectives for their effective management, thus addressing the research goal of enabling a more informed and systematic operationalization of AI applications.

6.3 Overall Theoretical Contribution

Based on the essays and their theoretical contributions in their entirety, my dissertation contributes also overarching to the academic discourse of AI management. Hence, the findings and contributions of my essays enable further theorizing about how researchers can understand AI specific management in different management domains. I propose the following model as a lens to derive and explain the need for AI management practices in a certain management domain (Figure 3):

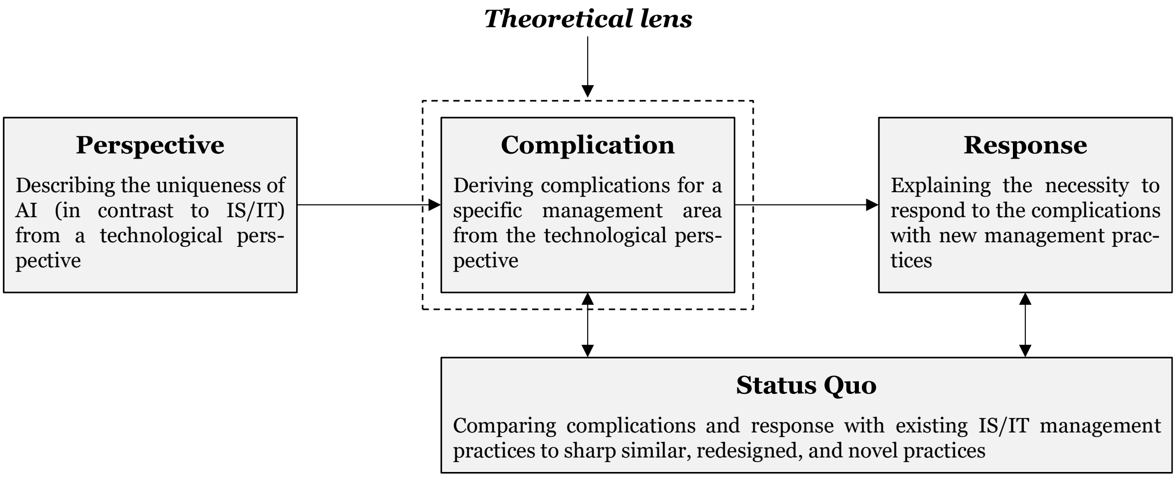

Figure 3. *Model for Deriving AI Management Practices*

The model begins with *Perspective*, which entails articulating the distinctive characteristics of AI that set it apart from traditional IS/IT. This initial framing is crucial for establishing the theoretical uniqueness of AI as a subject of management research. Building upon this foundation, the model suggests setting up *Complications*, where researchers derive specific challenges introduced by AI within a particular management domain. These complications emerge directly from the previously established technological distinctiveness of AI to highlight the inadequacies of existing management practices in addressing these AI-specific challenges. By employing a specific *Theoretical lens*, researchers can systematically examine how AI, as a unique technological artifact, challenges existing assumptions, reconfigures organizational practices, and necessitates novel management responses. The *Response* component follows, emphasizing the scientific and practical need to formulate novel or adapted management practices to address the identified complications. The *Status Quo* functions as a comparative lens, comparing the proposed complications and responses against prevailing IS/IT management challenges and practices. This comparison serves to emphasize whether the required responses represent incremental, redesigned, or entirely novel paradigms, thereby contributing to a deeper theoretical understanding and practical guidance for managing AI in organizational contexts.

To demonstrate the applicability of the model, I give two examples below (one example from my essays and one example from the current AI management literature). In my essay 4, I established the *Perspective* through the recognition of AI's distinct characteristics autonomy, learning, and inscrutability from Berente et al. (2021) and how they complicate innovation and decision-making in use case identification. The *Complication* is framed using the garbage can model (*Theoretical lens*), where technology-triggered choice opportunities, overwhelming variety, and non-obvious problem-solution matching create ambiguous and nonlinear decision processes during AI use case identification. The *Response* is the development and empirical testing of a method to structure AI use case identification, including actionable design principles tailored to organizational complexities. The *Status Quo* is critiqued as overly rigid and disconnected from the emergent, chaotic nature of AI innovation.

Vial et al. (2022) articulate a *Perspective* by distinguishing AI project management through the interplay of three logics: traditional project, agile, and AI workflows. These distinct practices highlight the unique nature of AI development. They then move to *Complication*, identifying eight tensions that arise from conflicts between these logics, such as differing notions of progress or deliverables, which challenge traditional project management practices. Their *Response* involves deriving four strategies to mitigate these tensions, such as rethinking "done" in AI projects or fostering collaborative

AI teams ("AI power couples"). The *Status Quo* is challenged by showing that existing IT/IS project management approaches are insufficient for AI's unique workflow demands, requiring hybrid and adaptive approaches. The *Theoretical Lens* of institutional logics enables the authors to conceptualize the AI management tensions and the necessity of reconciling conflicting norms in AI projects.

These two examples show an instantiation of the model and how the respective contributions can be presented clearly and sharply. I do not claim that this is the only way to position AI management practices in research. But I would like to encourage fellow researchers to ponder whether the above model is appropriate for their research projects. In this way, they can make a fruitful and targeted contribution to the growing scholarly corpus of AI management.

6.4 Practical Implications

Besides the theoretical contribution, the developed artifacts and frameworks also serve managers with various implications and help them to manage the integration of AI in their organizations. Regarding RG1, the findings of essay 1 offer managers a tool to evaluate the relevance of academic AI research for their specific organizational context and application scenarios. Overall, this essay offers actionable guidance for organizations seeking to develop a shared, context-sensitive understanding of AI by aligning theoretical insights with practical applicability, thereby addressing the ambiguity surrounding the concept of AI.

Regarding RG2, the findings of essay 2 offer managers a taxonomy as a structured tool to navigate, design, and assess AI strategies by organizing the strategic design space and identifying dominant strategic configurations with the help of the clusters derived. The findings of essay 3 offer managers a replicable method to integrate AI-specific considerations into organizational governance structures, enabling a more coherent and comprehensive AI transformation. The findings of essay 4 offer managers a method with a flexible and systematic approach to identifying AI use cases, emphasizing the importance of contextual relevance, structured decision-making, and interdisciplinary collaboration in maximizing AI's economic and innovative potential. Collectively, the essays deliver a coherent framework that supports managers in strategically managing AI applications by addressing critical challenges at the intersection of strategy, governance, and implementation, thereby aligning AI initiatives with organizational objectives in a structured and context-sensitive manner.

Regarding RG3, the findings of essay 5 offer managers a practical framework and instantiation for integrating LLMs into ideation processes, thereby enhancing both divergent and convergent phases of innovation while serving as a foundational guide for the structured application of LLM-based agents. The findings of essay 6 offer managers a practically applicable LLM-based architecture that enhances risk identification and mitigation by automating the analysis of unstructured data, supporting decision-making through actionable insights. The findings of essay 7 offer managers a structured approach to integrating AI into decision-support systems by addressing both technical and organizational challenges, such as stakeholder acceptance and operational impact, thereby facilitating effective and responsible AI integration. Collectively, the essays offer managers empirically grounded and context-sensitive design strategies for incorporating AI at the application level, highlighting the need to account for domain-specific characteristics, human-AI interaction, and organizational readiness to ensure effective and responsible integration of AI solutions.

Regarding RG4, the findings of essay 8 offer managers a structured approach to identifying and implementing critical steps for ensuring the ongoing functionality, reliability, and improvement of ML applications in their production environments. The findings of essay 9 offer managers a taxonomy as a structured tool to design LLM-based solutions for generating synthetic data and archetypes as a template for current approaches used to generate synthetic data. Collectively, the essays provide a comprehensive understanding of the operational challenges of AI, offering actionable guidance for practitioners to ensure the stable, effective, and sustainable operation of AI systems in practice, thereby advancing management of AI applications at an operations level.

6.5 Limitations

First, a central limitation of my dissertation lies in the ever-evolving nature of AI technologies. Given the rapid pace of innovation, especially in areas such as LLMs and autonomous decision systems, the frameworks and methods developed throughout my dissertation may face challenges in maintaining long-term relevance. Although the essays aim to address both fundamental characteristics and contemporary characteristics of AI, the findings are inherently anchored in the current state of technological capabilities and organizational practices. This temporal constraint means that future advancements could render certain assumptions or design recommendations partially outdated. Despite this limitation, the contributions remain valuable as they establish a structured foundation for understanding and managing AI integration, which can be iteratively refined in response to technological progress.

Second, a further limitation is the predominant reliance on qualitative research methodologies (e.g., semi-structured interviews, grounded theory approach, DSR). While these approaches enable in-depth exploration of complex, context-sensitive phenomena related to AI integration, they may limit the generalizability of findings across different organizational or industry settings. The emphasis on expert perspectives and case-specific data may introduce interpretive biases or contextual dependencies that may affect the broader applicability of the results. Despite this limitation, the qualitative approach provides rich, theory-informed insights and offers practical guidance grounded in real-world organizational dynamics, thereby enhancing the conceptual maturity of AI management research.

Third, a further limitation pertains to the evaluation settings, which primarily involve prototype implementations or test environments rather than fully operational deployments. Many of the proposed artifacts (e.g., the LLM-based agent systems, the governance framework) were assessed through simulated scenarios, expert feedback, or pilot interventions rather than longitudinal studies in real-world environments. This restricts the ability to evaluate the long-term robustness, scalability, and organizational impact of these interventions under real-world conditions. Despite this limitation, the prototype-based evaluations offer critical proof-of-concept validation and establish actionable starting points for future empirical testing and refinement.

Fourth, my dissertation does not claim to offer complete coverage of all relevant aspects within each of the three management levels. While the selected essays provide targeted insights into key challenges and opportunities, they necessarily prioritize depth over breadth due to practical constraints in scope and methodological feasibility. This selective focus may result in underrepresentation of certain issues or domains, such as AI-related cultural change, long-term value realization, or cross-functional coordination. Despite this limitation, my AI management framework still contributes meaningfully by advancing domain-specific knowledge and proposing structured interventions that can be expanded upon in future work.

6.6 Future Research

The findings and contributions of my dissertation provide fruitful avenues for future research in the field of AI management. In this context, I consider the following five topics to be essential points of departure for future research.

First, future Research should investigate if and how AI management practices further evolve in the context of AI agents. Although my essays 6 and 7 contain multi-agent systems, there is a need for further studies to investigate in more detail how to manage AI agents. In particular, questions about delegation from human agents to AI agents, AI agents to human agents, and AI agents to AI agents arise. Furthermore, it still remains unclear how managers need to (re)structure tasks to delegate them to AI agents or human agents, considering the strengths and weaknesses of both AI and human agents. For example, an experiment could provide insights into how a different restructure and delegation by managers to humans and AI agents affects the overall task performance.

Second, future research should include longitudinal studies that track organizations over time to evaluate the sustained effectiveness of AI management practices. Such studies can uncover the long-term outcomes, adaptations, and institutional learning processes that arise from AI management. These insights are critical for identifying which practices are most resilient and value-generating in dynamic environments. For example, a longitudinal case study could follow a multinational corporation's implementation of an AI strategy across multiple business units, assessing how governance structures, performance metrics, and cultural shifts contribute to or hinder the realization of AI's promised potential.

Third, there is a need for holistic, in-depth case studies that capture the full spectrum of AI integration across strategic, application, and operations management levels. The essays in my dissertation examine these levels in isolation, which limits understanding of how cross-level dependencies and feedback loops shape AI integration. Holistic observations could illuminate how organizations orchestrate alignment across management levels, manage tensions, and coordinate transitions. For example, a case study of a healthcare provider implementing AI from boardroom strategy through clinical decision-support systems to operational workflow automation would be valuable to gain insights into systemic, holistic AI integration.

Fourth, future research should expand the thematic scope within each AI management level to encompass unconsidered management domains. This includes, for instance, AI project management, AI portfolio governance, and diverse forms of human-AI interaction, particularly as domain-specific constraints vary significantly. Such explorations would enrich the granularity of AI management and support more tailored interventions. For example, researchers could investigate how human-AI collaboration manifests in highly regulated domains such as aviation, where trust, safety, and procedural rigor are inevitable, comparing it to less regulated contexts like marketing.

Fifth, future research should explore change management as it relates to the integration of AI across strategic, application, and operations levels. While my dissertation emphasizes technical and structural aspects, the success of AI integration also depends on how organizations manage shifts in roles, routines, and culture. Future studies could investigate how training or communication needs to be adapted at different management levels to support the integration of AI at each level. For example, a study could assess how employee training impacts the deployment of monitoring systems for AI applications at the operations level.

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Appendices

Appendix A: Declarations of Co-Authorship and the Individual Contributions

In this appendix, I outline the individual contributions of all my co-authors.

Essay 1: How to Consider the Artificial Intelligence Term? A Categorization System to Strengthen Research Impact

This research paper was co-authored by Moritz Schüll, Peter Hofmann, Dominik Protschky, and Abayomi Baiyere. The authors contributed as follows:

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. Therefore, his authorship is reflected throughout the entire research project.

Moritz Schüll (co-author)

Moritz Schüll contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Moritz Schüll prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Peter Hofmann (co-author)

Peter Hofmann contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology and analysis of the study data. Additionally, Peter Hofmann prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. Therefore, his authorship is reflected throughout the entire research project.

Abayomi Baiyere (co-author)

Abayomi Baiyere contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Essay 2: Conceptualizing the Design Space of Artificial Intelligence Strategy: A Taxonomy and Corresponding Clusters

This research paper was co-authored by Peter Hofmann, Simon Meierhöfer, Leon Müller, Anna-Maria Oberländer, and Dominik Protschky. The authors contributed as follows:

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Simon Meierhöfer (co-author)

Simon Meierhöfer contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Simon Meierhöfer prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Anna Oberländer (co-author)

Anna Oberländer contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Peter Hofmann (co-author)

Peter Hofmann contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Leon Müller (co-author)

Leon Müller supported the initial conceptualization of the research project, including the formulation of the research goals and aims. Additionally, Leon Müller engaged in critical review and revision of the manuscript.

Essay 3: Towards Systematic AI Governance - A Transformation Method

This research paper was co-authored by Dominik Protschky, Moritz Schüll, and Nils Urbach. The authors contributed as follows:

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Moritz Schüll (co-author)

Moritz Schüll contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Moritz Schüll prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Nils Urbach (co-author)

Nils Urbach contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Essay 4: Identifying Artificial Intelligence Use Cases - Towards a Method Facilitating Garbage Can Innovation Processes

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

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Peter Hofmann (co-author)

Peter Hofmann contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Peter Hofmann prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Nils Urbach (co-author)

Nils Urbach contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Christoph Buck (co-author)

Christoph Buck contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Jan Jöhnk (subordinate co-author)

Jan Jöhnk especially contributed to the project by introducing his methodological knowledge as well as mentorship throughout the research process.

Philipp Stähle (subordinate co-author)

Philipp Stähle especially contributed to the project by introducing his methodological knowledge as well as by occasionally supporting the data analysis throughout the research process.

Essay 5: Augmenting Divergent and Convergent Thinking in the Ideation Process: An LLM-Based Agent System

This research paper was co-authored by Leopold Fischer-Brandies, Simon Meierhöfer, and Dominik Protschky. The authors contributed as follows:

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. Furthermore, he was involved in the development of the research project's technical artifact. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Leopold Fischer-Brandies (co-author)

Leopold Fischer-Brandies contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Leopold Fischer-Brandies prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the development of the research project's technical artifact. Therefore, his authorship is reflected throughout the entire research project.

Simon Meierhöfer (co-author)

Simon Meierhöfer contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Simon Meierhöfer prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. Therefore, his authorship is reflected throughout the entire research project.

Essay 6: Leveraging Large Language Models for Information Extraction in Project Risk Management

This research paper was co-authored by Tobias Guggenberger, Felix Paetzold, Dominik Protschky, Jochen Kuhmann, and Rudolf Markus Petri. The authors contributed as follows:

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was responsible for the development of the research project's technical artifact and the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

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Felix Paetzold contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Felix Paetzold prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was responsible for the development of the research project's technical artifact. Therefore, his authorship is reflected throughout the entire research project.

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Jochen Kuhmann (co-author)

Jochen Kuhmann supported the research project by critical review, commentary, and revision of the manuscript. He also provided oversight throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Rudolf Markus Petri (co-author)

Rudolf Markus Petri supported the research project by critical review, commentary, and revision of the manuscript. He also provided oversight throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Essay 7: Integrating Artificial Intelligence into Football Refereeing: Insights from German Bundesliga Referees

This research paper was co-authored by Tobias Guggenberger, Daniel Feulner, and Dominik Protschky. The authors contributed as follows:

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Daniel Feulner (co-author)

Daniel Feulner contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Daniel Feulner prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Tobias Guggenburger (co-author)

Tobias Guggenburger contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Essay 8: What Gets Measured Gets Improved: Monitoring Machine Learning Applications in their Production Environments

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

Dominik Protschky (co-author)

Dominik Protschky contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Luis Lämmermann (co-author)

Luis Lämmermann contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology and analysis of the study data. Additionally. Luis Lämmermann prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. Therefore, his authorship is reflected throughout the entire research project.

Peter Hofmann (co-author)

Peter Hofmann contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Nils Urbach (co-author)

Nils Urbach contributed to the research project by critical review, commentary, and revision of the manuscript. He also provided oversight and mentorship throughout the research process. Therefore, his authorship is reflected throughout the entire research project.

Essay 9: Leveraging Large Language Models for the Generation of Synthetic Data

This research paper was co-authored by Dominik Protschky, Tobias Guggenberger, and Valentin Mayer. The authors contributed as follows:

Dominik Protschky (co-author)

Dominik Protschky contributed to this research project as a lead author. He contributed to the research project by conceptualization of the study, including the formulation of overarching research goals and aims. He was responsible for the design of the methodology, data collection, and analysis of the study data. Additionally, Dominik Protschky prepared the initial draft of the manuscript, created visualizations and presentations of the data, and engaged in critical review and revision of the manuscript. He was also responsible for the administration of the project. Therefore, his authorship is reflected throughout the entire research project.

Tobias Guggenberger (subordinate co-author)

Tobias Guggenberger especially contributed to the project by introducing his methodological knowledge as well as mentorship throughout the research process.

Valentin Mayer (subordinate co-author)

Valentin Mayer especially contributed to the project by introducing his methodological knowledge as well as by occasionally supporting the data analysis throughout the research process.

Appendix B: Further Scientific and Practical Publications

Title	Authors	Publication outlet
Developing Purposeful AI Use Cases: A Structured Method and Its Application in Project Management	Peter Hofmann, Jan Jöhnk, Dominik Protschky, Nils Urbach	International Conference on Wirtschaftsinformatik (WI)
A Systematic Literature Review on How to Improve the Privacy of Artificial Intelligence Using Blockchain	Sebastian Duda, Dorian Geyer, Tobias Guggenberger, Marc Principato, Dominik Protschky	Pacific Asia Conference on Information Systems (PACIS)
KI: Eine Aufgabe für das ganze Unternehmen	Nils Urbach, Peter Hofmann, Dominik Protschky	CIO Jahrbuch
KI-Anwendungsfälle zielgerichtet identifiziere	Peter Hofmann, Jan Jöhnk, Dominik Protschky, Philipp Stähle, Nils Urbach, Christoph Buck	Wirtschaftsinformatik & Management
KI-basierte Services intelligent gestalten: Einführung des KI-Service-Canvas	Nils Urbach, Björn Häckel, Peter Hofmann, Lukas Fabri, Sebastian Ifland, Philip Karnebogen, Stefanie Krause, Luis Lämmermann, Dominik Protschky, Moritz Markgraf, Lukas Willburger	Diskussionspapier ERef Bayreuth
Governance von künstlicher Intelligenz: Eine Methode zur Transformation vorhandener Governance-Mechanismen in Unternehmen	Dominik Protschky, Moritz Schüll, Nils Urbach	Wirtschaftsinformatik & Management

Table B1. *Overview over further scientific and practical publications*

Essay 1: How to Consider the Artificial Intelligence Term? A Categorization System to Strengthen Research Impact

Authors: Schüll, Moritz; Hofmann, Peter; Protschky, Dominik; Baiyere, Abayomi

Extended abstract: Artificial Intelligence (AI) has gained enormous momentum in both research and practice, becoming a strategic topic for business and society. Yet, despite its ubiquity, the AI term is applied inconsistently, often serving as a broad umbrella that encompasses diverse technologies, methods, and applications (Ågerfalk et al., 2022; Grashoff and Recker, 2023). This inconsistency has far-reaching implications: while AI promises innovation and transformation, the lack of conceptual clarity risks fragmenting scholarly contributions and impeding cumulative knowledge building (Monett and Lewis, 2018; Mikalef and Gupta, 2021). Addressing this ambiguity is crucial for the Information Systems (IS) field, where AI research can contribute to both theoretical advancement and societal discourse.

Despite decades of discussion, no universally accepted definition of AI has emerged (P. Wang, 2019; Russell and Norvig, 2016). Attempts at rigid definitions or classification systems quickly become outdated as AI technologies evolve, a challenge often described as the “AI effect” (Stone et al., 2022). Moreover, reliance on monolithic conceptualizations of AI causes information loss and hinders rigorous knowledge transfer across research streams (van Giffen et al., 2022). Scholars have therefore called for new approaches that acknowledge AI’s evolving, pluralistic nature (Berente et al., 2021; Collins et al., 2021). Against this backdrop, the guiding research question of this paper is: *How can we categorize and describe AI artifacts together with the associated activities to develop and use these artifacts?*

To answer this question, a systematic literature review of 368 publications across leading Information Systems and management journals, as well as proceedings of the International Conference on Information Systems was conducted (Kitchenham and Charters, 2007; Okoli, 2015). After careful screening, 282 relevant papers were analyzed using a Gioia-inspired coding approach (Gioia et al., 2013; Miles et al., 2014). Through iterative coding and synthesis, first-order concepts were distilled into themes

and, subsequently, into three aggregate dimensions. This process resulted in an extendable property-based categorization system. Rather than attempting to fix AI into static definitions, the system allows researchers to characterize their subjects through fluid, overlapping categories that reflect both technical and socio-technical properties.

The resulting categorization system advances AI research in several ways. First, it distinguishes three central dimensions (AI artifact, subject, and context) each comprising multiple themes and properties that capture the diversity of AI research (Grashoff and Recker, 2023). Second, it embraces a family resemblance perspective (Wittgenstein et al., 2009), acknowledging that AI-labeled research subjects may share few or no common characteristics, yet still belong to the same research "family." This flexible structure ensures adaptability to future developments in AI while avoiding the limitations of rigid taxonomies (Berente et al., 2021). Third, the system supports cumulative knowledge building by enabling researchers to specify what is genuinely new in their work, communicate the boundaries of their results, and foster comparability across studies (Ågerfalk et al., 2022). Ultimately, this contribution helps bridge conceptual gaps, reduces research inefficiencies, and strengthens the impact of IS research on the evolving AI discourse.

Keywords: Artificial Intelligence; definition; categorization system; family resemblance

Publication status: In preparation for submission

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Essay 2: Conceptualizing the Design Space of Artificial Intelligence Strategy: A Taxonomy and Corresponding Clusters

Authors: Hofmann, Peter; Meierhöfer, Simon; Müller, Leon; Oberländer, Anna-Maria; Protschky, Dominik

Extended Abstract: The rapid advancement of Artificial Intelligence (AI) has moved the technology to the core of corporate agendas, offering opportunities for intelligent products, novel services, and disruptive business models (Li et al., 2021). Against this backdrop, organizations are increasingly expected to establish a distinct AI strategy to secure competitive advantage, guide the implementation of AI projects, and align them with broader business goals (Keding, 2021). However, while practitioners emphasize the necessity of such strategies, the academic discourse on AI strategy remains nascent, especially when compared to well-established domains such as IT and digital strategy (Bharadwaj et al., 2013; Volberda et al., 2021). This raises the need for a systematic understanding of how organizations design and structure AI strategies as a response to AI-induced market and resource shifts (Enholm et al., 2022).

Despite consensus on the strategic relevance of AI, extant studies offer only fragmented insights into AI strategy. Prior research has focused on selective aspects, such as cognitive strategy (Davenport & Mahidhar, 2018), the convergence of AI and corporate strategy (Kitsios & Kamariotou, 2021), and the integration of AI into organizational strategy (Borges et al., 2021). While these contributions highlight the importance of AI in strategic management, they do not systematically elaborate on the design of an AI strategy, nor do they provide a shared understanding of its dimensions and manifestations (Reddy et al., 2022; Vomberg et al., 2023). As a result, both researchers and practitioners face difficulties in describing, analyzing, and classifying AI strategies across organizations. To address this shortcoming, the essay poses the following research question: *What is the design space of an AI strategy in the context of incumbent firms?*

To answer this question, the study adopts a taxonomy-building approach in line with design science research (Nickerson et al., 2013; Kundisch et al., 2022). Following iterative conceptual-to-empirical and empirical-to-conceptual procedures, the taxonomy

was developed across five iterations. Evidence was drawn from a structured review of scientific and professional literature, fifteen semi-structured expert interviews, and the analysis of 51 real-world AI strategy instances. The resulting taxonomy comprises 15 dimensions and 45 characteristics, systematically capturing the strategic responses organizations can pursue in light of AI-related challenges. Building on this taxonomy, a cluster analysis (Ketchen & Shook, 1996) identified four distinct archetypes of AI strategy (Technology Navigator, Innovation Explorer, Business Enhancer, and Operations Stabilizer) each representing a typical combination of strategic design choices.

From a theoretical perspective, this study establishes one of the first comprehensive frameworks to conceptualize the design space of AI strategy, thus enriching the discourse at the intersection of information systems and strategic management (Gregor, 2006; Gregor & Hevner, 2013). The taxonomy consolidates fragmented knowledge into a coherent structure and situates AI strategy in relation to established strategic concepts, highlighting its distinctive nuances (Bharadwaj et al., 2013; Pumplun et al., 2019). From a practical perspective, the taxonomy and clusters provide managers with a structured lens to design, evaluate, and refine AI strategies in line with firm-specific goals and constraints (van Giffen & Ludwig, 2023; Sagodi et al., 2024). By offering a shared understanding of AI strategy, the study advances both scholarly theorizing and real-world implementation, paving the way for future research on the evolution and performance of AI strategies.

Keywords: Artificial Intelligence; Strategy; Taxonomy; Clusters

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Essay 3: Towards Systematic AI Governance - A Transformation Method

Authors: Protschky, Dominik; Schüll, Moritz; Urbach, Nils

Abstract: The increasing integration of artificial intelligence (AI) applications into organizational processes has amplified the importance of AI governance. As AI technologies possess characteristics such as autonomy, self-learning, and opacity, they pose unique governance challenges that differ from traditional information systems (Papagiannidis et al., 2023; Schneider et al., 2023; Wirtz et al., 2022). Organizations must strike a balance between harnessing AI's potential for business value creation and addressing risks related to transparency, accountability, and fairness (Benbya et al., 2021; Papagiannidis et al., 2023). Against this backdrop, the question of whether existing IT governance frameworks can be adapted to accommodate AI-specific considerations has become a critical issue for both scholars and practitioners.

Despite increasing scholarly attention to AI governance, the field remains fragmented. Some argue that the distinct features of AI require tailored governance frameworks (Gasser & Almeida, 2017; Schneider et al., 2023), while others contend that existing IT governance models may suffice (Seppälä et al., 2021). However, the path toward systematically transforming existing frameworks to address AI remains unclear (Taeihagh, 2021). Current research rarely considers how established IT governance mechanisms can be adapted to account for AI's risks and opportunities (Mäntymäki et al., 2022; Birkstedt et al., 2023). This gap motivates the research question of this study: *How can organizations transform their governance frameworks towards systematic AI governance?*

To answer this question, the study employs a Design Science Research (DSR) approach (Hevner et al., 2004; Peffers et al., 2007). Building on theoretical insights from corporate and IT governance and AI governance literature, the authors develop AI governance transformation method. The method was iteratively designed using situational method engineering (Henderson-Seller & Ralyté, 2010), integrating knowledge from IT governance frameworks with empirical insights from qualitative interviews and focus groups with experts in AI and IT governance. The evaluation process combined ex-ante and ex-post assessments (Sonnenberg & vom Brocke, 2012; Venable et al., 2016) through three rounds of expert interviews, two focus groups, and practitioner workshops with 30 participants across different industries.

The findings reveal that AI governance cannot be treated as a standalone governance unit but must be integrated into existing structures. The developed transformation method provides organizations with a structured, iterative process comprising four steps: defining entry points for AI governance, deriving necessary governance mechanisms, evaluating costs and benefits, and aligning AI governance with corporate governance structures. Importantly, the results demonstrate that successful AI governance requires organization-wide transformation strategies rather than localized departmental initiatives. The contribution of this research is twofold: theoretically, it bridges AI and IT governance by positioning AI governance as an evolutionary extension of established governance frameworks; practically, it offers actionable guidance for managers and consultants to embed AI considerations within existing governance structures. In doing so, this study advances the discourse on AI governance by offering a systematic method for organizational transformation grounded in both theory and practice.

Keywords: AI governance, design science research, IT governance, governance transformation

Publication status: In preparation for submission

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Essay 4: Identifying Artificial Intelligence Use Cases – Towards a Method Facilitating Garbage Can Innovation Processes

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

Abstract: Artificial intelligence (AI) technologies hold extensive potential for driving innovation, efficiency, and competitiveness across industries (Magistretti et al. 2019). However, leveraging this potential requires organizations to identify promising AI use cases that align with strategic goals and generate value (Hofmann et al. 2020; Brunnbauer et al. 2021; Russell and Norvig 2016). Unlike conventional technologies, AI's unique characteristics of autonomy, learning, and inscrutability (Berente et al. 2021) create uncertainty in organizational decision-making. As organizations face continuously evolving technological frontiers, they encounter challenges such as technology momentum-triggered choice opportunities, overwhelming variety of potential applications, and non-obvious problem-solution matching (Grebe et al. 2023). These dynamics render the identification of AI use cases a highly complex decision-making process that demands structured yet adaptive methodological guidance.

While several nascent methods exist to guide AI use case identification (Hofmann et al. 2020; Sturm et al. 2021), empirical evidence regarding their efficacy remains limited. Existing approaches, such as use case canvases, prioritization matrices, and quality assurance frameworks (Brunnbauer et al. 2021; Grebe et al. 2023; Sturm et al. 2021), provide valuable structure but often assume linearity and overlook the chaotic and emergent conditions under which organizations must make decisions. This raises the unresolved question of how methods can effectively support decision-making in contexts characterized by uncertainty, dynamic change, and diverse stakeholder involvement. Thus, this study addresses the research question: How to design a method for efficacious decision-making in AI use case identification?

To answer this question, we adopted an Action Design Research (ADR) approach (Sein et al. 2011) in collaboration with EnBW, one of Europe's largest energy suppliers. The ADR process unfolded in four stages: problem formulation, building-intervention-

evaluation, reflection and learning, and formalization of learning. Over the course of a six-month project, we conducted 17 expert interviews across industries and engaged deeply in EnBW's organizational context. Iterative interventions, including workshops, semi-structured interviews, and field observations, enabled us to adapt and refine a methodological artifact starting from Hofmann et al.'s (2020) initial framework. Drawing on the garbage can model (Cohen et al. 1972), we conceptualized AI use case identification as an "organized anarchy" where problems, solutions, participants, and choice opportunities dynamically intersect.

Our results provide both practical and theoretical contributions. At EnBW, the method facilitated the identification of seven viable AI use cases ranging from process improvements to the exploration of new business fields, one of which ("business navigator for technical operations of wind farms") was implemented and achieved 45–57% more economically optimized maintenance scheduling decisions compared to manual planning. Beyond this intervention, we derived six design principles to address AI-specific complications: iterative scoping with termination options, dimensioning according to demand, contextual embedding of solutions, efficient search strategies, data experiments, and employing a cognitive function lens. These principles extend existing literature by explicating how methodological guidance can balance rigor and pragmatism, integrate organizational knowledge, and support adaptive decision-making in AI use case identification. Ultimately, this study contributes a method and accompanying design principles that enhance organizations' ability to systematically and effectively respond to AI's elusive potential, thereby advancing both innovation management theory and practice.

Keywords: artificial intelligence; use case identification; decision-making; garbage can model; methodological guidance; action design research

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Essay 5: Augmenting Divergent and Convergent Thinking in the Ideation Process: An LLM-Based Agent System

Authors: Fischer-Brandies, Leopold; Meierhöfer, Simon; Protschky, Dominik

Abstract: The rise of Generative Artificial Intelligence (GenAI) and, in particular, Large Language Models (LLMs) has generated growing interest in innovation management due to their capacity to support the generation of creative and novel ideas (Epstein et al., 2023; Nah et al., 2023). LLMs are increasingly recognized as powerful tools for language comprehension and generation, finding application in machine translation, text summarization, and content creation (Bouschery et al., 2023; Hacker et al., 2023). Their ability to enhance human creativity and productivity (Kanbach et al., 2023) makes them highly relevant for knowledge-intensive processes such as ideation, a crucial activity for organizations to sustain competitiveness in dynamic environments (Kohli & Melville, 2019; Ali et al., 2020). As innovation fundamentally relies on both divergent thinking—exploring a wide range of possibilities—and convergent thinking—developing and evaluating those ideas (Bánáthy, 1996; Griebel et al., 2020; Müller-Wienbergen et al., 2011)—understanding how to harness LLMs to augment these processes becomes a central concern.

Despite the promise of GenAI for creativity support, extant research on AI in innovation management has predominantly focused on isolated tasks such as trend forecasting, customer requirement analysis, or knowledge graph construction (Wang et al., 2022; Wu et al., 2022; Dessi et al., 2021). This fragmented view has left a gap in understanding how LLMs can comprehensively support the full ideation process (Bouschery et al., 2023). While scholars have theorized about the potential of LLMs to impact ideation along the double diamond design process (Bouschery et al., 2023), concrete approaches for their practical utilization remain scarce. Calls for research have therefore emphasized the need to design and instantiate artifacts that demonstrate how LLMs can augment individual creativity in idea generation (Griebel et al., 2020; Nah et al., 2023). Against this backdrop, this study addresses the research question: How to design an LLM-based agent system that augments the ideation process?

To answer this question, we followed the Design Science Research (DSR) paradigm (Peffers et al. 2007; Hevner et al., 2004; March & Smith, 1995). First, we conducted a structured literature review to derive design objectives from prior work in AI and innovation management. We then designed and instantiated an artifact—an LLM-based agent system for ideation—that operationalizes both divergent and convergent thinking. The architectural model consists of multiple specialized agents (e.g., problem definer, brainstormer, evaluator, reporter) organized into user and AI agent layers, allowing dynamic interaction and contextual adaptation. The instantiation was implemented using Python and Microsoft's AutoGen library, connected to GPT-4 Turbo. Evaluation followed a four-stage process (Sonnenberg & vom Brocke, 2012), including iterative refinement, prototyping, and rigorous testing. Finally, we validated the artifact through ten semi-structured expert interviews across industries such as automotive, healthcare, and software (Myers & Newman, 2007).

The results confirm the utility of the system in supporting divergent and convergent thinking. Experts emphasized the value of features such as feedback mechanisms, external data integration, recombination of information, and iterative refinement of ideas. The system was recognized as adaptable to different contexts and capable of generating more breadth and depth in idea generation compared to traditional approaches. At the same time, limitations emerged concerning evaluation comprehensiveness, privacy considerations, and the need for user training. The study contributes theoretically by instantiating the theorized potential of LLMs in ideation (Bouschery et al., 2023) and enriching DSR knowledge on socio-technical artifacts (Gregor & Hevner, 2013). Practically, it provides innovation managers with actionable design objectives and a blueprint for integrating LLM-based systems into ideation processes. Overall, the artifact demonstrates that LLMs can effectively augment human creativity, helping organizations sense opportunities and generate strategically relevant ideas in an increasingly dynamic innovation landscape.

Keywords: Generative Artificial Intelligence, Large Language Models, Innovation, Ideation Process.

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Essay 6: Leveraging Large Language Models for Information Extraction in Project Risk Management

Authors: Protschky, Dominik; Paetzold, Felix; Guggenberger, Tobias; Strüker, Jens; Kuhmann, Jochen; Petri, Markus-Rudolf

Abstract: Effective project risk management (PRM) is central to the success of complex projects, yet organizations continue to struggle with timely and proactive risk identification. Modern projects are characterized by structural intricacy, dynamic environments, and socio-political interdependencies, which exacerbate uncertainty and make risk detection particularly challenging (PMI, 2024; Vidal, Marle, & Bocquet, 2011). Traditional methods rely heavily on structured data and formal reporting, but early warning signals often first appear in informal, unstructured sources such as emails or meeting minutes (Afzal, Yunfei, Nazir, & Bhatti, 2021). This creates a detection gap between the emergence of risks and their formal recognition, undermining the ability of project managers to take proactive measures. Against this backdrop, recent advances in artificial intelligence, particularly Large Language Models (LLMs), offer new opportunities for processing unstructured textual and speech data, making them promising candidates for enhancing risk identification in PRM (Nah, Zheng, Cai, Siau, & Chen, 2023; Xu et al., 2024).

Despite LLMs' growing success in domains such as healthcare, finance, and manufacturing (Dagdelen et al., 2024; Thirunavukarasu et al., 2023; Matthes, Guhr, Krockert, & Munkelt, 2024), their application to PRM remains underexplored. Existing LLM-based information extraction (IE) methods typically assume stable information patterns, whereas PRM environments are highly dynamic and context-dependent, with risk indicators evolving throughout a project's lifecycle (Cagliano, Grimaldi, & Rafele, 2015). Current approaches thus fall short in accommodating ambiguous, asynchronous, and shifting project signals. This reveals a critical research gap: how to design an LLM-based information extraction system tailored to PRM's unique requirements. Accordingly, the guiding research question of this paper is: How can an LLM-based information extraction system be designed to extract relevant project risk indicators?

To address this question, the study adopts a Design Science Research (DSR) approach (Gregor & Hevner, 2013; Peffers et al., 2007). The process followed six iterative steps,

beginning with a comprehensive literature review and semi-structured expert interviews to identify design objectives (DOs) for effective risk-related information extraction (Okudan, Budayan, & Dikmen, 2021). Based on these DOs, we developed a layered architecture consisting of an input layer for multi-source data integration, an extraction layer with aggregation, orchestration, and specialized risk agents, a storage layer for structured risk information, and an output layer providing dashboards and proactive alerts. The artifact was demonstrated through a prototype implementation using Python, SQLite, and a Streamlit dashboard, integrating multiple LLMs such as Llama 3.3 and Mistral 7B. The architecture was evaluated through four distinct activities, including ex-ante literature analysis, expert interviews, prototype testing, and an ex-post focus group with domain experts (Sonnenberg & vom Brocke, 2012).

The results show that the proposed architecture effectively addresses the challenges of dynamic and unstructured PRM data. It enables proactive detection of emerging risks, continuous monitoring across diverse data sources, and systematic integration of human expertise through feedback loops. The prototype demonstrated the feasibility of specialized risk agents for identifying financial, technical, and stakeholder-related risks, while focus group validation highlighted the system's utility for real-world PRM contexts. The contributions of this study are threefold. First, it extends the theoretical understanding of LLM-based IE by adapting it to volatile project environments. Second, it advances PRM practice by bridging the detection gap between informal signals and formal risk documentation. Third, it conceptualizes and validates a multi-agent architecture that operationalizes LLMs for collaborative and context-aware risk extraction. In doing so, the paper provides both theoretical insights and practical implications for more effective, proactive project risk management (Li et al., 2024; Willumsen et al., 2024).

Keywords: Project risk management, risk identification, information extraction, large language models

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Essay 7: Integrating Artificial Intelligence into Football Refereeing: Insights from German Bundesliga Referees

Authors: Guggenberger, Tobias; Feulner, Daniel; Protschky, Dominik

Abstract: The growing integration of artificial intelligence (AI) into professional sports has transformed performance analytics, broadcasting, and fan engagement, with refereeing now emerging as a particularly critical application domain. In football, refereeing decisions directly influence match outcomes, league standings, and financial returns, while being subject to immense pressure and scrutiny (Vögele & Schäfer, 2019; The Guardian, 2024). Yet, referees face inherent challenges such as fatigue, crowd influence, and split-second judgments, leading to an error rate of around 14% (Mallo et al., 2012; Brand et al., 2009; Nevill et al., 2002). To address these limitations, football has introduced technologies like goal-line systems and the Video Assistant Referee (VAR), increasingly drawing on AI for data-driven support (Errekagorri et al., 2020; Karanasios et al., 2023). As leagues and federations strive to enhance decision accuracy, fairness, and transparency, AI offers unprecedented potential for rapid, unbiased support—yet its integration raises complex technical, social, and ethical questions.

Despite the recognized promise of AI, prior research has predominantly focused either on technical development (e.g., machine learning–based systems for ice hockey or squash refereeing) or on conceptual discussions of fairness and human judgment in officiating (Jiang & Bao, 2022; Ma & Kabala, 2024; Da Silva et al., 2024). However, studies rarely address how AI can be effectively embedded into referees' decision-making processes while preserving game flow, referee authority, and stakeholder trust (Gottschalk et al., 2020; Samuel et al., 2021; Li et al., 2023). This lack of a holistic socio-technical perspective leaves unresolved tensions between technological efficiency and the human essence of refereeing. Accordingly, this study asks: What are the influencing factors in integrating AI-based decision support for football referees?

To investigate this question, we employed a qualitative research design, conducting fifteen semi-structured interviews with sixteen experts, including referees from the

German Bundesliga and UEFA, officials from the German Football Association, and AI specialists. Guided by established interview protocols for decision-support research (Myers & Newman, 2007; Walters, 2011), the interviews explored both current technological pilots and future scenarios for AI-assisted refereeing. In total, over 450 minutes of data were recorded and analyzed using inductive coding based on the Gioia methodology (Gioia et al., 2013). This approach enabled us to derive structured insights into referees' expectations, perceived risks, and requirements for AI integration, moving beyond purely technical considerations toward a socio-technical framework.

The findings highlight five core factors shaping AI-supported decision-making: (1) technical prerequisites such as reliable data input and workflow integration, (2) regulation of AI usage through standardized and ethical guidelines, (3) the referee–AI relationship, balancing decision-making power and preserving referee authority, (4) game impact, ensuring smooth flow and attractiveness, and (5) stakeholder acceptance, hinging on trust, transparency, and communication (Gottschalk et al., 2020; Held et al., 2023; Zhekambayeva et al., 2024). Together, these factors provide a socio-technical framework for AI integration that emphasizes collaboration rather than substitution of referees. The study contributes by offering empirical insights from elite referees' perspectives, underscoring the importance of trust, fairness, and contextual awareness in AI-assisted refereeing. For practice, the framework delivers actionable guidance to sports organizations and technology developers, showing how AI can be integrated to enhance accuracy and consistency without eroding the human and cultural foundations of football refereeing.

Keywords: AI in sports, Football refereeing, Decisions support systems (DSS), Human-AI collaboration

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Essay 8: What Gets Measured Gets Improved: Monitoring Machine Learning Applications in their Production Environments

Authors: Protschky, Dominik; Lämmermann, Luis; Hofmann, Peter; Urbach, Nils

Abstract: The increasing adoption of machine learning (ML) across industries has brought with it the challenge of sustaining reliable performance when applications move from development into production environments. In practice, organizations deploying ML systems frequently face issues such as model drift, inaccuracies, and biases that may only emerge after deployment, especially in dynamic, customer-facing contexts (Lamarre et al. 2024; Singla et al. 2024). Such shortcomings can lead to reputational harm, regulatory risks, and business losses if not addressed promptly. Consequently, robust monitoring has become a cornerstone of ensuring the long-term reliability, compliance, and value creation of ML applications in production (Benbya et al. 2020; Klaise et al. 2020).

Despite its importance, research into ML monitoring remains underdeveloped. While frameworks such as MLOps have advanced the automation and orchestration of ML workflows, they provide only limited guidance on the specifics of monitoring ML applications. Most prior studies either address monitoring only superficially as part of the ML lifecycle or focus narrowly on technical aspects such as drift detection (Nunes and Guedes 2024; Lewis et al. 2022). This leaves organizations without clear, systematic practices for handling the complex interplay between technical, organizational, and environmental factors in production settings. To address this gap, this paper poses the guiding research question: What are relevant practices for monitoring ML applications in their production environments?

To answer this question, we employed a rigorous qualitative, mixed-method approach. First, we conducted a multivocal literature review of both academic and practitioner-oriented sources, following the guidelines of Ogawa and Malen (1991) and Garousi et al. (2016), which yielded 25 academic and 56 practitioner articles. Second, we complemented these findings with ten semi-structured interviews of experienced ML

engineers and data scientists across industries, recruited via professional networks and conferences, until saturation was achieved. Third, we reviewed 15 existing ML monitoring tools to triangulate insights and contrast theoretical and practical approaches. For data analysis, we applied coding techniques by Corbin and Strauss (1990) and Saldaña (2021) to systematically identify categories of practices and challenges.

Our findings contribute both to theory and practice. We first propose a conceptual framework grounded in intelligent agent theory (Russel and Norvig 2016; Wooldrige and Jennings 1995), outlining five characteristics of ML production environments that shape monitoring requirements. Based on this, we derive 17 monitoring practices: 14 practices organized along a typical quality management cycle (define, measure, assess, act, control) and three cross-sectional practices emphasizing proactive adaptation, continuous learning, and tailoring to use cases. These practices provide organizations with actionable guidance on how to define relevant monitoring metrics, identify and analyze drift, adapt models and processes, and institutionalize iterative improvements. The paper thus advances academic discourse by systematically conceptualizing ML monitoring and offers practitioners a structured framework to mitigate risks and enhance the reliability of ML systems in production.

Keywords: Machine Learning; MLOps; Monitoring; Software Engineering

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Essay 9: Leveraging Large Language Models for the Generation of Synthetic Data

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Abstract: The digital transformation of organizations and societies increasingly relies on the availability of high-quality data to fuel innovation, decision-making, and system development. However, challenges such as data scarcity, high acquisition costs, and strict privacy regulations often limit access to sufficient real-world data (Fonseca & Bacao, 2023; Ramos & Subramanyam, 2021). Synthetic data, generated artificially to mimic the statistical properties of real data, offers a promising alternative to overcome these barriers. Recently, Large Language Models (LLMs) have emerged as powerful tools for generating synthetic datasets that are scalable, contextually rich, and adaptable across domains (Choenni et al., 2023; Goyal & Mahmoud, 2025; Li et al., 2023b). Their capacity to generate realistic, domain-specific datasets—such as synthetic patient records in healthcare—demonstrates their potential to enhance research and practice while safeguarding privacy (Blanco-González et al., 2023; Giuffrè & Shung, 2023).

Despite these promising developments, research on LLM-based synthetic data generation remains fragmented, with limited conceptual clarity and no unified framework for understanding the multitude of design options. Prior studies have highlighted specific challenges and applications—for example, the epistemological implications of synthetic data in the social sciences (Rossi et al., 2024), comparative reviews of generative models (Smolyak et al., 2024), and domain-specific implementations in healthcare (Ibrahim et al., 2025). However, what is lacking is a systematic perspective that organizes existing approaches and identifies recurring patterns. This absence of a structured overview inhibits both scholarly understanding and practical decision-making. Against this background, the guiding research question of this paper is: What are the potential and currently applied design options for utilizing LLMs to generate synthetic data?

To answer this question, the paper adopts a taxonomy development methodology following Nickerson et al. (2013). The study iteratively combined conceptual-to-empirical and empirical-to-conceptual approaches, drawing on a structured literature review, expert interviews and focus groups, and an analysis of 94 real-world software artifacts. This iterative process led to the identification of 13 dimensions and 35 characteristics

across four layers: objectives, LLM configuration, generation process, and output. The taxonomy was empirically validated through classification of real-world cases, ensuring both theoretical robustness and practical relevance. In a subsequent step, cluster analysis was applied to derive archetypes that represent dominant approaches in practice, thereby offering a higher-level synthesis of the diverse design options.

The results contribute a comprehensive taxonomy and four archetypes—Practical Generalist, High-Capacity Specialist, Rapid Deployment Solver, and Enriched Data Expert—that capture prototypical configurations of LLM-based synthetic data generation. This taxonomy provides conceptual clarity to a fragmented research landscape and offers actionable guidance to practitioners, enabling them to navigate trade-offs regarding scalability, privacy, bias management, and cost-efficiency. By doing so, the study advances theoretical knowledge by laying the groundwork for further analysis and prediction of synthetic data strategies (Gregor, 2006), while also supporting responsible and effective applications in practice. Ultimately, this work contributes to the democratization of synthetic data generation and highlights future directions for expanding into multimodal domains and addressing ethical challenges such as bias and transparency (Lozoya et al., 2023; Rossi et al., 2024).

Keywords: Large Language Model, Synthetic Data, Data Generation, Taxonomy, Archetypes

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