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Enable AI, AI Enables

Toward Autonomous, Economically Acting Machines

Dissertation

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Copyright Statement

The following sections are partly comprised of content taken from the research papers included in this thesis. To improve the readability of the text, I omit the standard labeling of these citations.

Abstract

The emergence of the machine economy (ME) characterized by autonomous entities capable of economically motivated action and collaborative value creation presents organizations with major challenges and opportunities. Currently, there are pivotal developments toward machine autonomy which is key for the ME, e.g., through advances in artificial intelligence (AI). However, many organizations are still struggling to effectively develop and integrate AI into their operations. A major obstacle to exploit AI's potential is data scarcity, which hinders training, optimization and scaling of AI systems.

The overarching aim of this thesis is to guide organizations toward the ME by improving AI development. This is addressed by investigating how to enable organizations to manage AI development resources more efficiently, how to enable organizations to mitigate AI's data scarcity issue through distributed machine learning (DML), and how to understand the path toward the ME. The presented research is structured as a series of six essays. The first essay conceptualizes AI development through a resource portfolio perspective, examining how investments affect outcomes. The second essay proposes a research agenda focused on the implementation of privacy-enhancing technologies in AI development. The third and fourth essays design, implement and evaluate DML approaches in specific application contexts to overcome data scarcity, i.e., essay three implements a federated prescriptive process monitoring approach whereas essay four proposes a split learning architecture to collaboratively improve demand forecasting in supply chains. The fifth essay constructs a comprehensive five-layer model capturing the functionality and potential of ME entities. Lastly, the sixth essay develops a maturity model of ME entities which draws the path toward the emerging ME.

This thesis contributes to research by addressing various research gaps by providing prescriptive and design knowledge for AI development as well as presenting a unified understanding of the ME. In conclusion, the thesis strives to enable AI for organizations and sheds light on how AI enables the emerging machine economy.

Keywords: Artificial intelligence, machine learning, distributed learning, machine economy, autonomous machines, information systems, sociotechnical systems

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Introduction to Enable AI, AI Enables: Toward Autonomous, Economically Acting Machines

Abstract

This thesis aims to guide organizations toward the ME by improving AI development. Comprising six essays, the thesis addresses three research goals: (1) enable organizations to manage AI development resources more efficiently, (2) enable organizations to mitigate AI's data scarcity issue through DML, and (3) understand the path toward the ME.

In the following introduction, I motivate the overall relevance of the research (section 1), provide the relevant background from the literature (section 2), deduce the three research goals and the essay's research questions (section 3), outline the research methodology implemented in the essays (section 4), summarize the essays (section 5), discuss the findings and conclude the introduction (section 6).

Keywords: Artificial intelligence, machine learning, distributed learning, machine economy, autonomous machines, information systems, sociotechnical systems

Table of Contents – Introduction

1 Introduction

Advancements in emerging digital technologies are reshaping how value is generated (Baier et al., 2023; Guggenberger et al., 2021). The significant progress in emerging technologies such as artificial intelligence (AI), internet of things and distributed ledger technologies, equips machines with yet unseen abilities – such as economic value transfers, independent transaction processing, and adaptive learning behaviors (Ågerfalk, 2020; Jöhnk, Albrecht, et al., 2021; Schweizer et al., 2020). As machines become more autonomous and capable of economical decision-making, they are being integrated into economic processes (Jöhnk, Albrecht, et al., 2021). One refers to the machine economy (ME), when autonomous machines engage in economic interactions and value creation (Hartwich et al., 2023). In the ME, machines are not just tools controlled by humans but independent economic agents that can autonomously engage in transactions and make decisions traditionally reserved for human agents (Hartwich et al., 2023; Jöhnk, Albrecht, et al., 2021).

Recent advances of AI technologies have allowed for the emergence of human-like perceived systems (Alavi et al., 2024; Epley et al., 2007). The AI's human-like perception and capabilities reduce the divide between the social and technical system (Bostrom and Heinen, 1977b; Jain et al., 2021; Li and Suh, 2021). As a result, AI breaches the monopoly of the humans' agency (Ågerfalk, 2020; Jöhnk, Albrecht, et al., 2021). The blurring of the social and technical systems poses new challenges for information systems (IS) research as it undermines the established concepts of strictly separated systems (Bostrom and Heinen, 1977b). Yet, there is no common understanding among academics and practitioners that can serve as a basis for exploring this paradigm shift.

Once primarily considered in computer science research, AI has now taken a central role in IS research as its technologies become increasingly applicable in practice (Gomes et al., 2019). The current attention towards AI is fueled by the growing recognition of AI's transformative potential across industries (Gupta and George, 2016). The rapid advancement and democratization of AI have sparked interest across industries and academia alike. Academics and practitioners attribute an immense potential to AI for the transformation of products, processes, and business models (Furman and Seamans, 2019). Driven by recent developments, many organizations are eager to participate in the AI-hype, but despite their ambitions, they struggle to convert their efforts successfully into economic returns (Agrawal, Gans, et al., 2018).

Advances in hardware contributed to the democratization of AI and significantly lowered the entry barriers, making them accessible to organizations of all sizes (Dally et al., 2018; Jordan and Mitchell, 2015). Further, as data is another key factor for successful AI development (Verleysen and François, 2005). The increased availability of data – from sensors in smart factories to transactional data in financial systems – has accelerated the development and increased the performance of AI solutions (Jordan and Mitchell, 2015; Taylor, 2024). However, while data availability is improving, many organizations still face challenges related to data scarcity. Organizations struggle to collect sufficient data to develop AI, particularly in niche industries or domains where high-quality data is difficult to obtain (Gao et al., 2022). Due to privacy concerns and policies, organizations cannot share their raw data to conjointly improve their AI development. Besides artificially generating data (Albrecht et al., 2024; Ashmore et al., 2021), distributed data sets can be used to train a better model (McMahan et al., 2017). Emerging privacy-enhancing technologies (PET), such as distributed machine learning (DML), offer approaches to overcome these barriers.

While the ME is emerging, organizations still lack the knowledge to exploit the underlying technologies, illustrated by AI as an example. To propose a solution to the aforementioned issues, the aim of the thesis is to enable organizations to use AI and thereby facilitate organizations for the ME. Thus, this thesis addresses the following overarching research aim:

Guide organizations toward the ME by improving AI development

I worked on six essays to address this aim. In the beginning, I focused on enabling organizations to develop and integrate AI. The first essay analyzes the impact of resource investments on the AI lifecycle. This essay aims at providing a guideline for decision-makers on how to purposefully invest to shape a technical subsystem that suits the social system's requirements. To address data scarcity, the second essay analyzes the current body of knowledge regarding PETs in AI development. Using this essay as a foundation, essays 3 and 4 instantiate specific use-case-driven software artifacts implementing previously identified PETs tackling data scarcity. Thereby, essays 2, 3 and 4 aim to improve the technical system and increase its ability to fulfill assigned tasks. After enabling organizations to exploit AI, I focus on the emerging ME, which is mainly enabled by the advances of AI. Furthermore, in essays 5 and 6, I gave an outlook on the emerging ME, where the rigorous separation between the social system and the technical system becomes indistinct.

The remainder of this thesis is structured as follows: First, I introduce the relevant concepts in section 2. Second, I discuss the research goals (RG) and research questions addressed in this thesis and how I derived them from the previously stated research aim in section 3. Third, I state the research methodologies used in the essays in section 4. Fourth, I summarize the results of my research structured along the essays in section 5. Fifth, I conclude the thesis by discussing results, limitations and future research opportunities in section 6. Lastly, the essay's (extended) abstracts follow the introduction.

Throughout this thesis, I use "we" rather than "I" because each essay represents a collaboration of various co-authors. Details of the specific contributions of each co-author for all essays can be found in Appendix A. Parts of this introduction include material from the original research articles. Thus, I've removed standard citation markers to make the text more readable.

2 Background

In this section, I will describe the background of my thesis. First, I introduce the sociotechnical system (STS), which serves as overarching theoretical foundation. Second, I will define AI respective ML. Third, I will introduce their respective specialties in distributed applications. In the last section, I will present concept of the ME.

2.1 Sociotechnical system

To provide a solid conceptual foundation for the remainder of this thesis, I will use the STS as a theoretical basis. The STS is an established theory and widely used in IS research (Sykes et al., 2014). The STS describes an IS as the combination of a social and a technical system, as shown in Figure 1 (Chatterjee et al., 2020; Trist and Bamforth, 1951). The combination of both systems results in a unified value-creating system (Bostrom and Heinen, 1977a,b). In order to optimize the STS as a whole, it is crucial to understand both systems as well as their interplay and to jointly optimize the subsystems (Oosthuizen and Pretorius, 2014).

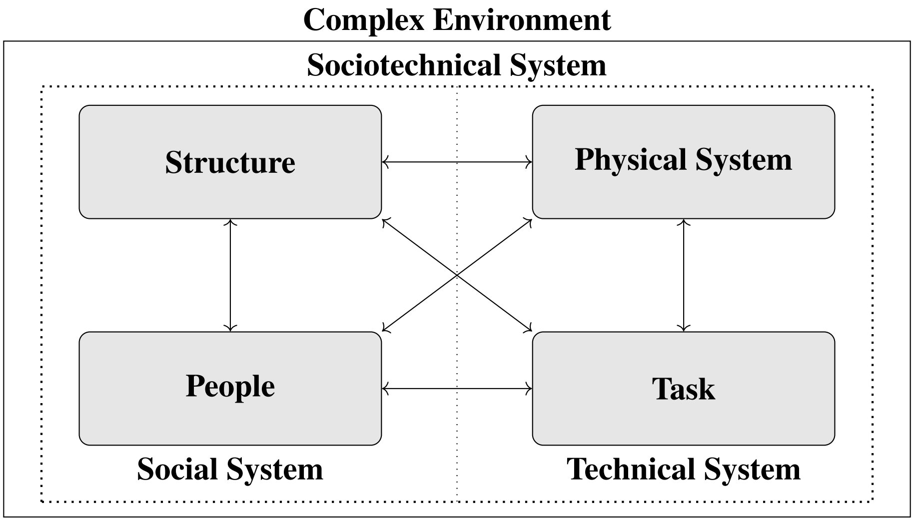

Figure 1: Sociotechnical system (Bostrom and Heinen, 1977a,b)

The social system represents the conventional organizational perspective along with the respective *structure* (e.g., organizations, hierarchy, processes) down to the individual *people* (e.g., people's cognitive and social behavior, their knowledge as well as their needs) (Oosthuizen and Pretorius, 2016). The social system describes how people are organized and work together (Eijnatten, 2013). It includes the relationships between individuals and teams, their interactions and their norms of behavior (Pasmore, 1988).

The technical system consists of a *physical system* (e.g., devices, software) that works on a certain *task* (Oosthuizen and Pretorius, 2016). The technical system uses the physical system (e.g., diagnostic system in healthcare) to process an input into an output (e.g. x-ray image as input and diagnosis as output) (Sykes et al., 2014). While the social system can shape the technical system, the technical system uses technology to serve a human purpose (Arthur, 2007). The interplay between the social and technical systems is rather iterative (Shani et al., 1992). The systems cannot be developed independently of each other. Each adaptation of one system must fit the other in order to be effective (Herbst, 1976; Mumford, 2000).

2.2 Artificial intelligence

In this thesis, I focus on AI-enhanced and AI-enabled systems as physical system. One approach to build an AI is to implement ML (Ågerfalk et al., 2020; Campesato, 2020). ML is a technology that strives *"to learn from experience E with respect to some class of task T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E"* (Mitchell, 1997, p. 2). Other approaches to AI include rule-based expert systems and fuzzy logic (Kühl et al., 2022; Russell and Norvig, 2016; Rzepka and Berger, 2018). ML introduces a new paradigm to implement IS (Koza et al., 1996; Kühl et al., 2022). While, the former main task was to implement concrete instructions (e.g., algorithms and data structures) with ML, the new main task focuses on configuring ML approaches and data-driven training (e.g., selecting and augmenting data, as well as executing and monitoring the training process) (Agrawal, Arya, et al., 2019; Amershi et al., 2019; Ashmore et al., 2021).

AI has become central to IS research as its technologies find increasing practical application (Gomes et al., 2019). Research strives to bring AI into application and to integrate it into existing and new IS, resulting in AI-enhanced and AI-enabled systems (Rzepka and Berger, 2018). IS research also recognizes the use of ML in decision support systems – supporting humans with additional intelligence – to maximize the hybrid system's performance compared to both humans and ML alone (Arnott, 2006; Arnott and Pervan, 2005; Hunke et al., 2022; Müller et al., 2016; Power et al., 2019).

Organizations are already generating business value through the use of ML applications across various industries, creating competitive pressure on those who fall behind (Agrawal, Gans, et al., 2018). Today's organizational environment is characterized by high volatility and a fiercely competitive landscape (Kreuzer et al., 2020). Yet, some organizations are struggling to implement AI-enabled IS to create value (Agrawal, Gans, et al., 2018). In terms of STS, organizations fail to effectively shape the technical system in a way to harmonize with the social system. Decision-makers must decide how to invest available resources to maximize the technical system's performance in solving the selected task. To guide decision-makers in advancing the technical system, IS research proposed ML lifecycles (Agrawal, Arya, et al., 2019; Amershi et al., 2019; Ashmore et al., 2021).

The focus of technical research relies on advancing the technical system's performance. While the original focus was improving model training, the focus has increasingly shifted towards preparatory data management (Ashmore et al., 2021; Whang et al., 2021). *"One of the key ingredients in a successful development of learning algorithms is therefore to have enough data for learning [...]"* (Verleysen and François, 2005, p. 4). The availability of data is key to successfully training an ML model (Russell and Norvig, 2016) and the quality and quantity of available data, thus, is a main lever to improve the development of ML models (Verleysen and François, 2005). Accordingly, there are an increasing number of tools that help to improve the exploitation of existing data (Albrecht et al., 2024; Dao et al., 2019; Hirt and Kühl, 2018; McMahan et al., 2017).

2.3 Distributed machine learning

One approach to increase data availability is to use data from distributed data sources, i.e., multiple organizations (Jin et al., 2024; Wen et al., 2022). But, there are various reasons why the data is not easily shared (such as laws or regulations (Liu, Huang, et al., 2022) and trade secrets (Zhu, Liu, et al., 2019)). Thus approaches are needed to maintain data confidentiality while using them for ML training (Hirt and Kühl, 2018; Hirt, Kühl, et al., 2023). While traditional, local learning is limited to the data's availability on a single device, DML involves coordinating the training process across multiple devices (Hard et al., 2018). Approaches capable of collaborative training on distributed data sources are called DML (Jin et al., 2024; Karnebogen et al., 2023; Thapa et al., 2022). DML describes an ML paradigm that strives to mitigate data scarcity compared to the local model training while providing privacy benefits compared to centralizing distributed data (Jin et al., 2024). In short, DML is a technique that allows different clients (e.g., enterprises) to collaboratively learn an ML model without sharing raw data (McMahan et al., 2017).

One of the most prominent members of DML is federated learning (Konečný et al., 2016; Konečný et al., 2017; Li, Fan, et al., 2020; Liu, Nie, et al., 2021) which has been applied in various domains such as telecommunications (Brik and Ksentini, 2020), healthcare (Nguyen et al., 2023), and the energy sector (Tun et al., 2021). In federated learning, a client trains an ML model, such as a neural network on their local data. Thereafter, the collaborating clients share their models and aggregate them into a global model which promises better performance than the locally trained model (Bonawitz, 2019; McMahan et al., 2017; Wen et al., 2022; Zhang et al., 2021). Another prominent member of DML promising better privacy protection is split learning (Gupta and George, 2016; Romanini et al., 2021; Thapa et al., 2022; Vepakomma et al., 2018), which has been applied to theft detection in power grids (Alromih et al., 2022) and healthcare (Muhammad et al., 2021; Poirot et al., 2019). Split learning exploits the successive nature of computation in a neural network, allowing computations to be distributed across multiple computational nodes (Vepakomma et al., 2018). In contrast to federated learning, the necessity of sharing entire models is void and, depending on the architecture, only embeddings or gradients between the so-called cut layer are shared.

When implementing DML, the participants can profit from others' data without accessing their raw data. However, there are attacks that aim on deriving the raw data (Shokri et al., 2017). An encouraging countermeasure against such attacks is the use of further PETs, such as differential privacy or homomorphic encryption (Soykan et al., 2022). Depending on the use case, different technological approaches can be selected. First, there are statistical approaches (i.e., differential privacy) that add noise to the raw data, obfuscating their original value. Second, there are cryptographic approaches (i.e., homomorphic encryption) that encrypt and thereby obfuscate the data while enabling others to apply operations and calculations to the data. While their use is established in technical research, there is only little managerial and design knowledge regarding the integration of PETs in IS.

2.4 Machine economy

The previously described developments of AI enable more mature applications (Alter, 2020). As a result, intelligent agents are emerging (Berente et al., 2021; Kühl et al., 2022) that can purposefully act in an environment (Alter, 2020; Schleiffer, 2005). They have the ability to operate autonomously in various contexts, such as energy services (Li, Pan, et al., 2021), financial markets (Arifovic et al., 2022; Nuti et al., 2011), or smart cities (Musso et al., 2019). As AI systems, such as large language models and generative AI, become more sophisticated, particularly in understanding and generating human-like language, autonomous machines can seamlessly interact with other machines and humans (Verma et al., 2016). These advances reflect an emerging paradigm further fueled by rapid progress of internet of things (Leminen et al., 2020) and distributed ledger technologies (Guggenberger et al., 2021). The resulting autonomy, combined with advances in other emerging technologies, allows machines to communicate, transact, and make economic decisions independently (Lee, Olson, et al., 2010; Panarello et al., 2018). This emerging concept is called ME (Hartwich et al., 2023; Königs, 2019). While today's machines act on direct orders and in dependence on humans (as humans' agent), the ME promotes a concept in which machines act autonomously (Ågerfalk, 2020). As technology continues to evolve, they are fundamentally reshaping the way we conceptualize and engage in economic systems – blurring the boundaries between machines as tools and agents of economic activity (Ågerfalk, 2020; Hollebeek et al., 2021). These developments motivate the broader concept of the ME, where machines are not just tools but active participants in value creation (Schlecht et al., 2020; Urbach et al., 2020).

Like the conventional economy, the ME consists of interacting agents that collaboratively create value (Macías-Escrivá et al., 2013). In the ME, these agents are not only human actors but also autonomous machines (Jöhnk, Weißert, et al., 2021; Schuetz and Venkatesh, 2020) that can easily interact with other agents regardless of them being humans or machines (Akhtar et al., 2021; Mercan et al., 2022). In contrast to our current economy, which is characterized by centralization and intermediaries, the ME includes concepts such as decentralization and the autonomy of participants (Miehle et al., 2019; Schweizer et al., 2020).

The emergence of the ME not only transforms the way how machines and humans interact, but also poses new challenges for research. Economically autonomous acting machines are new in economic theory (Hartwich et al., 2023; Schuetz and Venkatesh, 2020). In terms of STS, besides the need to advance the technical system, due to the autonomous nature of the emerging technical system, the rigorous separation between the social system and the technical system might become indistinct. With the emergence of the ME, the monopoly of agency of the social system is broken up (Ågerfalk, 2020; Jain et al., 2021; Jöhnk, Albrecht, et al., 2021; Schuetz and Venkatesh, 2020). This not only entails technical changes but also raises ethical and legal questions about the responsibility of machines and their actions (Ågerfalk, 2020).

3 Research goals

In this section, I will present my approach to addressing the thesis' research aim. Based on the research aim, I derive my RGs. Afterward, I describe each RG and explain how I derived the essay's research questions.

To address my thesis' research aim – *guide organizations toward the ME by improving AI development* – I proceeded threefold and derived the following RGs:

RG1: Enable organizations to manage AI development resources more efficiently

RG2: Enable organizations to mitigate AI's data scarcity issue through DML

RG3: Understand the path toward the ME

First, I aim at bridging the gap between the social and the technical systems, by guiding decision-makers on how to purposefully invest during the organization's AI adoption. Research addressing the first RG revealed that data scarcity is a significant challenge in AI development (Verleysen and François, 2005). Thus, second, I strive to propose new approaches to AI adoption issues and focus on mitigating adoption barriers from a technical viewpoint. After Afterward, I focus on the emerging concept of the ME, where I take an unified perspective on both systems.

All essays in this thesis strive to contribute twofold, practically and theoretically. While some papers tend to focus more on the academic contribution (i.e., essay 2 and essay 5), other papers focus on proposing a practical tool (i.e., essay 3 and essay 6). The essays draw on the literature from the technical domain (i.e., Khan et al., 2021; Vepakomma et al., 2018) and from IS (i.e., Agrawal, Gans, et al., 2018; Ashmore et al., 2021; Jöhnk, Albrecht, et al., 2021). The aim of the essays is to contribute to both literature streams, but with a clear focus on IS literature. To ensure the research's relevance and the clear description of the problem, I make use of the work of Maedche et al. (2019) and Herwix and Haj-Bolouri (2021).

To give an overview over my research endeavor, Table 1 shows how my essays address each RG. Besides the stated essays, I worked on and published further papers. Appendix A contains a list of all papers published during my doctorate. In the following subsections, I will describe each RG in detail and derive the research questions answered in the corresponding essays.

Table 1: Overview over RGs and the related essays and their outlets

Research Goal	Essay
RG1: Enable organizations to manage AI development resources more efficiently	**Essay 1**: Systematizing the Effects of Machine Learning Resources: An ML Lifecycle Perspective Published in: Business Information Systems Engineering (VHB JQ3: B, Scopus: 93%)
RG2: Enable organizations to mitigate AI's data scarcity issue through DML	**Essay 2**: Enabling Privacy and Collaboration: The Role of Privacy Enhancing Technologies in the Future of Artificial Intelligence Submitted to: Technological Forecasting and Social Change (VHB JQ3: B, Scopus: 99%) **Based on**: A systematic literature review on how to improve the privacy of artificial intelligence using blockchain Published in: Proceedings of the Pacific Asia Conference on Information Systems (VHB JQ3: C, Scopus: N.A.)
	Essay 3: Toward Data-Sovereign Prescriptive Process Monitoring: A Federated Learning Approach Submitted to: European Conference on Information Systems (VHB JQ3: B, Scopus: N.A.)
	Essay 4: Designing Effective Collaborative Learning Systems: Demand Forecasting in Supply Chains Using Distributed Data Under Review at: European Journal of Information Systems (VHB JQ3: A, Scopus: 99%)
RG3: Understand the path toward the ME	**Essay 5**: Understanding the Machine Economy: Combining Findings from Science and Practice Published in: International Journal of Innovation and Technology Management (VHB JQ3: C, Scopus: 54%)
	Essay 6: Forecasting the Emerging Machine Economy: Toward a Maturity Model Submitted to: Technological Forecasting and Social Change (VHB JQ3: B, Scopus: 99%)

3.1 Enable organizations to manage artificial development development resources more efficient

In today's rapidly evolving technological landscape, organizations must embrace AI to remain competitive (Gomes et al., 2019). In order to capitalize on AI's benefits, organizations must establish efficient AI development capabilities (Makarius et al., 2020). While hiring additional ML experts is an obvious investment, there are various other resources that can enhance AI development capabilities that might be more cost-efficient, such as advanced computational infrastructure and data augmentation tools. Decision makers have to differentiate the various investment possibilities to effectively allocate the organization's resources. E.g., having sufficient computational power can sometimes be more critical than investing in data augmentation tools. Researchers still lack knowledge on what resources are relevant for the development of AI and what effect investments in these resources have. As a result, despite the relevance, managers lack guidance on where to allocate resources most effectively. Therefore, research into the required resources for AI development is essential to provide organizations with the insight needed to make informed investment decisions and optimize their AI initiatives.

To address the lack of guidelines, in the first essay, we ask:

How do resource investments impact the ML lifecycle?

This question aims to help decision-makers improve their organization's resource allocation in order to effectively exploit AI's potential.

3.2 Enable organizations to mitigate artificial intelligence's data scarcity issue through distributed machine learning

By addressing the previous RG, I shed light on organizations' possibilities to enable the usage of ML. However, as described in the first essay and by Verleysen and François (2005), one of the major issues when implementing ML applications is data scarcity. In the following chapter, I will address this issue in multiple ways.

As detailed in the background chapter, while sufficient data often exists, it is frequently distributed across different organizations or departments and not available. This distribution poses a significant barrier to the development of AI applications, as data cannot be easily shared due to regulations and confidentiality concerns (Li, Wen, et al., 2021). These legal and managerial constraints limit the ability to consolidate data, thereby tightening the issue of data scarcity in AI development. Emerging PETs offer a promising solution to this challenge. Techniques such as DML, homomorphic encryption, and secure multi-party computation enable organizations to collaborate and share data without exposing sensitive information (Soykan et al., 2022). By allowing data to remain in its original location while still contributing to collective insights, PETs address both the need for data sharing as well as the constraints to keep the data confidential. Current research on mitigating data scarcity with PETs is predominantly technical and focuses on isolated use cases. While these studies advance the technical feasibility of PETs, they often neglect the broader IS perspective. There is a lack of comprehensive research examining how these technologies can be effectively integrated into organizational processes, governance structures, and strategic decision-making. This gap highlights the necessity for an IS-oriented exploration of PETs in addressing data scarcity. An IS perspective would not just consider the technology's design and implementation but also the strategic and managerial implications. Thus, in the second essay, we ask:

What is the status quo of research on PET-enhanced AI systems and services?
What are future research opportunities for IS research regarding PETs for AI systems and services?

This question aims to synthesize existing technical research and identify areas where IS researchers can contribute to, guiding organizations in leveraging PETs to enhance their AI capabilities.

In the previous essay, we identified a critical need for further IS research on utilizing PETs to address data scarcity in AI development. A prime example that highlights this necessity is business process management. Business process management strives to provide methods and tools to ensure that organizational processes run both effectively and efficiently (Baiyere et al., 2020; Dumas et al., 2018; Park and van der Aalst, 2022). Business process management exploits data like process logs to generate insights and improve the organization's processes. Therefore, it is an excellent example, where an organization can benefit from others' insights but must avoid sharing confidential process data. One focus area of business process management is prescriptive process monitoring, where the process is optimized during its execution (Fahrenkrog-Petersen et al., 2022; Kubrak et al., 2022). Implementing prescriptive process monitoring in an interorganizational context can lever significant benefits, but also introduces significant challenges. The necessary data for effective prescriptive process monitoring is distributed across multiple organizations, each with their own data sovereignty concerns and reluctance to share sensitive information. To overcome this, we designed a data-sovereign approach for interorganizational prescriptive process monitoring. This approach enables organizations to collaboratively generate qualitative suggestions without compromising their control over proprietary data. By leveraging PETs, we can facilitate secure collaboration that respects each organization's data sovereignty. With this application in mind, in the third essay, we ask:

How can we design a data-sovereign approach for interorganizational prescriptive process monitoring?

This question aims to explore how we can integrate distributed data sources in order to share valuable insights without raw-data sharing, exemplarily implemented for prescriptive process monitoring.

Another example that highlights the necessity of sharing data is the mitigation of the bullwhip effect in supply chain management – a common problem in IS research. The bullwhip effect refers to the phenomenon where small fluctuations in consumer demand lead to increasingly larger variances in orders placed upstream, causing inefficiencies and increased costs (Forrester, 1961). The established approach to mitigate the bullwhip effect is to share data along the supply chain (Lee, Padmanabhan, et al., 1997). However, there are conditions where the data is not shared. In these cases, accurate demand forecasting is key (Chen et al., 2000). Achieving this requires access to comprehensive, high-quality data that is often distributed among various organizations in the supply chain (Zhu, Ninh, et al., 2021). Due to competitive pressures and confidentiality concerns, these organizations are reluctant to share proprietary data, leading to data scarcity despite its distributed availability. By employing DML – enabled by PETs like split learning – organizations can collaboratively use demand forecasting models without sharing confidential data. Thus, in the fourth essay, we ask:

How can distributed collaborative machine learning be designed to enhance demand forecasting in supply chain management?

This question seeks to explore the design of collaborative AI solutions that respect data privacy while addressing a significant IS challenge. It aims to bridge technical PET research with IS' perspective on organizational collaboration, ultimately contributing to more efficient and responsive supply chains. The paper's contributions serve as a foundation for practitioners how to collaboratively work on confidential data to improve (demand) forecasting.

3.3 Understand the path toward the ME

After shedding light on how organizations can implement AI and how to design AI to have a bigger impact through the use of distributed data, I now want to give an outlook on the emerging ME. More and more autonomous machines will emerge (Jöhnk, Albrecht, et al., 2021), a trend that can already be seen (Mercedes Benz AG, 2023).

As machines become more autonomous, they will ultimately be autonomously engaged in value creation (Baier et al., 2023; Hartwich et al., 2023). The concept of machines participating autonomously in economic activities has been gaining attention. Despite the looming relevance, the scientific community has yet to reach a consensus on how to define or conceptualize the phenomenon of the ME. The lack of agreement originates from different points of view on and the fast-paced development of the ME. These varying perspectives underscore the necessity for a comprehensive conceptualization that unifies both theoretical and practical viewpoints. To conciliate the various developments, in the fifth essay, we ask:

How can the ME be conceptualized?

This question seeks to develop a unified understanding that encapsulates the various functions and capabilities of economically autonomous machines. By addressing this question, we aim to unify the perspective of academics with the perspective of practitioners and lay the groundwork for future research in this transformative area by providing a unified understanding of the ME.

After having established a unified understanding of the ME and its entities, it is essential to focus on how to actualize and mature the ME entities. To bridge the gap between theory and practice, there is a need to explore the maturation process of ME entities and identify the specific capability areas these entities must develop. Understanding how ME entities can mature will help to outline the stages of development and the progression of their functionalities. This includes examining how these entities can enhance their autonomy, decision-making abilities, and interactions within economic systems. Thus, in the sixth essay, we ask:

How can machine economy entities mature?

Which capability areas do machine economy entities have?

These questions aim to assist not only practitioners by offering a guideline for building applications within the ME, but also forecast emerging ME entities for researchers and policymakers.

4 Research design

In this section, I describe the methodologies applied in the six essays within this thesis. Each essay adopts a methodological approach tailored to its research questions and objectives. By employing a combination of quantitative, qualitative, and mixed-methods approaches, the methodological triangulation provides a solid foundation for the essays' findings. Table 2 gives a brief overview over the implemented methods. The following section will discuss the methods in greater detail.

Table 2: The essays' research methods

	Essay	Method
RG1	Essay 1	Design science research • Five iterations to develop a framework for decision-makers. • Systematic literature review following Webster and Watson (2002) to derive the first iteration. • 12 interviews to incorporate further insights and evaluate the framework.
RG2	Essay 2	Systematic literature review • Systematic literature review following Webster and Watson (2002). • Aral et al.'s (2013) organizing framework as structural element for the identified literature. • Identification of premature research areas and derivation of potential research avenues.
	Essay 3	Design science research • Design science research approach following Peffers et al. (2007). • Development of split learning approach in four iterations. • Simulation based quantitative evaluation using synthetic and real-world data.
	Essay 4	Design science research • Design science research approach according to Peffers et al. (2007). • Purely technical artifact evaluation strategy following Venable et al.'s (2016) FEDS framework. • Quantitative evaluation using augmented data.
RG3	Essay 5	Interview study • Systematic literature review following Webster and Watson (2002) to derive ex-ante propositions. • Coding of 14 interviews to test the propositions and derive ex-post propositions. • Transfer of the ex-post propositions into a layer model.
	Essay 6	Maturity model development • Iterative development of the maturity model following Becker et al. (2009). • Incorporating insights from literature, an academic focus group discussion and 14 interviews. • Evaluation of the maturity model with 8 interviews.

In the essay "*Systematizing the Effects of Machine Learning Resources: An ML Lifecycle Perspective*", we employed the design science research (DSR) paradigm to develop and evaluate a framework that helps decision-makers to improve their organization's resource allocation for AI development. We developed the framework in five design iterations, guided by the DSR methodology proposed by Peffers et al. (2007). Initially, we conducted a systematic literature review following Webster and Watson (2002) to build a foundational understanding of the ML lifecycle and the strategic value of resources, drawing insights from the resource-based view as the theoretical lens (Barney, 1991; Bharadwaj, 2000; Grant, 1991). Complementing this theoretical foundation, we performed an empirical analysis through twelve expert interviews with professionals in the field of ML. We selected the interviewees carefully in order to bridge the social and technical system (Herbst, 1976). These interviews were key in identifying relevant resources, their interdependencies, and their effects on the ML lifecycle. Each iteration of our design process refined the framework based on the combined insights from the literature and empirical evidence. Using interviews and Sonnenberg and vom Brocke's (2012) evaluation criteria, we validated the framework. Our approach bridges software engineering and management perspectives, contributing both theoretical and practical insights into effective ML management (Gregor and Hevner, 2013).

In the essay "*Enabling Privacy and Collaboration: The Role of Privacy Enhancing Technologies in the Future of Artificial Intelligence*", we conceptualize the research area of PETs-enhanced AI systems using Aral et al.'s (2013) organizing framework. The organizing framework is put forward to structure knowledge in an IS context (Gramlich et al., 2023; Risius and Spohrer, 2017). The framework consists of two dimensions: first, so called level of analysis – typical roles in IS (Lee, Krishnan, et al., 2020) – and so called activities – typical IS perspectives (Aral et al., 2013). After a comprehensive literature review (Kitchenham and Charters, 2007; Mikalef et al., 2018; Webster and Watson, 2002), we clustered the relevant literature (41 papers) into the organizing framework, to identify clusters that were in the focus of research and which were not yet relevant in literature. In addition, we summarize the current state of research, which has a focus in the technical domain. Based on these findings, we derive three key areas of interest demanding further research from the literature. Using these as foundation, we again draw on Aral et al.'s (2013) organizing framework to derive a future research agenda. Lastly, we propose two research endeavors that could bring PETs-enhanced AI systems into application.

In the essay "*Toward Data-Sovereign Prescriptive Process Monitoring: A Federated Learning Approach*", we adopted the DSR paradigm (Peffers et al., 2007) to develop a data-sovereign framework for prescriptive process monitoring. As DSR's aim is to develop novel and innovative IT-artifacts (March and Smith, 1995), we identified DSR as a suitable methodological approach to develop the DML approach. Our approach focused on utilizing federated learning to enable interorganizational collaboration while preserving data sovereignty. The research process began with a comprehensive literature review and the identification of challenges associated with data privacy and interorganizational process mining. We conceptualized and implemented a federated learning artifact designed to aggregate insights from distributed event logs without requiring the centralization of the raw data. A proof-of-concept prototype was instantiated to demonstrate the framework's viability. This prototype was evaluated in terms of its ability to provide actionable runtime recommendations for process optimization across multiple organizations. The evaluation included both qualitative and quantitative measures to assess the artifact's performance in addressing privacy concerns while fostering collaborative learning. To ensure the rigor of our findings, we rely on Venable et al.'s (2016) FEDS framework and conduct a quantitative evaluation of our artifact.

In the essay "*Designing Effective Collaborative Learning Systems: Demand Forecasting in Supply Chains Using Distributed Data*", we utilized a DSR paradigm (Peffers et al., 2007) to conceptualize and evaluate a DML artifact for demand forecasting in supply chain management. Analogous to the previous essay, DSR is the method of choice for this research endeavor. This methodology involved multiple phases, beginning with the conceptualization of the problem domain and the identification of design objectives. We analyzed existing approaches in DML to identify gaps, particularly in the context of distributed multi-task learning with strict privacy requirements. Exploiting the advantages of split learning, we developed a collaborative artifact that preserves data privacy while facilitating information sharing across a supply chain level. The effectiveness of the artifact was assessed through discrete agent-based simulations, where its performance in improving forecasting accuracy was evaluated under various supply chain scenarios using both synthetic and real-world data. We measured outcomes using metrics like mean squared error and mean absolute error to validate its improved forecasting capabilities. This iterative development and testing process integrated in Venable et al.'s (2016) FEDS framework evaluated the artifact's satisfaction of the design requirements, offering insights into its practical applicability for collaborative forecasting. Evaluating the artifact, we focused on the technical risk and efficacy evaluation strategy. In addition, we conducted a focus group workshop to adjust the advancement of the technical system with the social system's requirements (Herbst, 1976). The research was accompanied by Tuunanen et al.'s (2024) echelon DSR approach to ensure valid intermediate artifacts.

In the essay "*Understanding the Machine Economy: Combining Findings from Science and Practice*", we conducted a mixed-methods approach to investigate the ME, combining insights from a systematic literature review and qualitative interviews. First, a systematic review of literature in relevant databases identified existing research on the ME, forming the basis for six ex-ante propositions. Next, we conducted 14 semi-structured interviews with experts across diverse industries, focusing on the convergence of AI, internet of things and blockchain technologies. These interviews were analyzed through an iterative coding process using MAXQDA software to refine the initial propositions (Corbin and Strauss, 1990). Using the insights from the interviews, we partially revised our ex-post propositions. Based on the ex-post propositions as a foundation, we developed a five-layer model of the ME. This model represents the functional architecture required for interactions and transactions of autonomous machines. The iterative combination of theoretical and practical perspectives ensured a unified understanding of the ME's emerging dynamics, contributing to both academic discourse and industry application.

In the essay "*Forecasting the Emerging Machine Economy: Toward a Maturity Model*", we followed the established maturity model development methodology outlined by Becker et al. (2009) to create the Machine Economy Entities Maturity Model (MEEMM). The research process combined a systematic literature review with 22 qualitative interviews conducted with industry experts and researchers. The literature review provided the theoretical foundation for identifying six dimensions and eleven sub-dimensions relevant to ME entities. The qualitative interviews served to validate and refine these dimensions, enabling the iterative development of a maturity model that accounts for diverse stakeholder perspectives. Further, we applied Waymo's robotaxi use case to the MEEMM to assess its applicability. To conclude the paper, we evaluated our maturity model against the general design principles of Röglinger and Pöppelbuß (2011). This methodologically founded approach in developing the maturity model shows a clear path toward the emerging ME.

5 Summarizing the results

In order to guide organizations toward the ME by improving AI development, I have conducted a series of research projects in the form of the already mentioned essays. Each essay addresses the overall research aim and one of the previously defined RGs and further provides both theoretical insights and practical solutions. In this subsection, I will summarize the results of the six essays and explain how they address the thesis' research aim.

5.1 Essay 1: Systematizing the effects of machine learning resources: a machine learning lifecycle perspective

In the first essay, we identified 30 distinct resources essential for the development of AI applications, including raw data, data augmentation tools, and other vital elements across the ML lifecycle. By applying the resource-based view as a theoretical lens, we systematically analyzed the relationship among these resources. This analysis enabled the creation of the *Machine Learning Effects Framework*, which maps these resources and elucidates their interdependencies throughout the ML lifecycle. Furthermore, we identified six distinct effects of resource investments, then categorized them into direct and indirect effects, and provided new insights into the strategic impacts of resource allocation.

Essay 1 contributes to the academic discourse by deriving a portfolio view of AI resources, systematically categorizing and mapping them along the ML lifecycle. This novel framework bridges the gap between software engineering and management literature, offering a structured approach to resource optimization in AI development. Moreover, the essay introduces actionable insights on resource interdependencies and their strategic effects, which have been previously underexplored. Practically, the research provides a decision-support tool for organizations to make informed and efficient resource allocation decisions. By understanding how resources interact and influence the ML lifecycle, managers can optimize investments by reducing inefficiencies. Additionally, the essay offers policymakers a foundation for preventing monopolistic behaviors by democratizing access to essential AI resources.

In conclusion, this essay aligns with the overarching aim to guide organizations toward the ME by improving AI development by addressing the specific RG to enable organizations to manage AI development resources more efficiently. It provides the tools and knowledge necessary to optimize resource utilization, thus improving organizational readiness and capability to leverage AI technologies. Further, we derived effects of investments in resources, that help researchers and decision makers to prioritize investments. By doing so, it contributes on how to invest more efficiently into the technical system and, by mapping the investments to the ML lifecycle, how the investments affect the interplay of the social and the technical systems.

5.2 Essay 2: Enabling privacy and collaboration: the role of privacy enhancing technologies in the future of artificial intelligence

In the second essay, we explore the role of PETs in mitigating AI's data scarcity. Using Aral et al.'s (2013) organizing framework as structural element, we investigate the literature and provide a summary of the state-of-the-art research. We identified three key areas, that require more research as the socio-economic aspects of PET integration remain underexplored and organization are unable to assess the impact of integrating PETs in AI development. To conclude the essay, we use Aral et al.'s (2013) framework to derive a comprehensive research agenda.

Essay 2 identifies three critical areas of interest. First, it introduces the "PETs4AI Trilemma", which conceptualizes the inherent trade-offs between privacy, model performance, and resource efficiency in PET-enabled AI systems. Balancing these dimensions is a central challenge for practitioners and researchers alike. Second, the essay emphasizes the need to measure privacy generically as a continuum rather than a binary concept. Despite the increasing relevance of privacy, research lacks a universally accepted metrics for measuring privacy. Third, it highlights the importance of economic evaluations, recognizing the complexities in assessing the costs, benefits, and regulatory compliance associated with PET adoption. Organizations hesitate to integrate PETs because the benefits and challenges of the adoption cannot be sufficiently estimated. Lastly, we derived a comprehensive research agenda, to mitigate the identified issues in adopting PETs for AI systems.

By aligning technical and socio-economic perspectives, this essay aligns with the overarching research aim of the thesis. The essay serves as a foundation for the following essays to address the RG to enable organizations to mitigate AI's data scarcity issue through DML. It equips practitioners with insights into PETs-enhanced AI systems and what to consider when integrating PETs into the organization's AI development. Further, the essay is a foundation for future research to address critical challenges, ensuring the broader adoption and impact of PETs in AI development.

5.3 Essay 3: Toward data-sovereign prescriptive process monitoring: a federated learning approach

In the third essay, we designed and instantiated an innovative architecture for distributed collaborative prescriptive process monitoring, emphasizing data sovereignty and privacy. Our approach integrates prescriptive insights from prescriptive process monitoring with federated learning to enable organizations to share actionable process insights without exposing sensitive process logs. A proof of concept was realized in the form of a software artifact that operationalizes federated prescriptive process monitoring. This artifact was evaluated using synthetic data, demonstrating the feasibility and functional capabilities of the system in preserving privacy while optimizing processes collaboratively across organizations.

Essay 3 bridges two critical domains – DML and business process management. The essay's key contributions include the following: We set up the understanding of distributed prescriptive process monitoring and contributed to the academic discourse on privacy-preserving interorganizational collaboration. Through qualitative and quantitative evaluations, we validated the feasibility and benefits of our approach in enabling cross-organizational process optimization. By proposing an improved technical system for prescriptive process monitoring, our research provides a pathway to enhance the overall performance of STS. This system leverages federated learning to address privacy concerns while enabling richer insights from interorganizational data.

This essay aligns with the overarching research aim and the specific RG to enable organizations to mitigate AI's data scarcity issue through DML. By enabling organizations to collaboratively derive process optimizations without compromising data sovereignty, we demonstrate how to overcome the fundamental barrier by leveraging distributed AI solutions. The development of this federated prescriptive process monitoring framework directly contributes to the goal of unlocking interorganizational value while mitigating risks associated with data sharing.

5.4 Essay 4: Designing effective collaborative learning systems: demand forecasting in supply chains using distributed data

In the fourth essay, we derived a set of design objectives for cooperative DML and proposed an innovative architecture that leverages split learning, its u-shaped configuration, long short-term memory models, and multi-task ML techniques. These components were combined to address the challenge of collaborative demand forecasting in supply chain management while maintaining data confidentiality. Quantitatively, the architecture was evaluated across 30 distinct market scenarios using both synthetic and real-world datasets. The results demonstrated significant improvements in demand forecasting accuracy under varying supply chain and market conditions. Qualitative evaluation further outlined constraints and scenarios where the approach is most effective, providing a comprehensive view of its applicability.

Essay 4 makes several contributions to both academia and practice. The essay proposes a novel architecture for distributed multi-task ML that respects data privacy while facilitating collaboration across competitive organizations. We instantiate the architecture as a software artifact, demonstrating how integrating data from distributed sources improves demand forecasting. Further, we show how this approach mitigates the bullwhip effect and enhances overall supply chain efficiency by improving forecasting accuracy and synchronization, while keeping sensitive demand data confidential, thus ensuring its practicality in competitive environments.

By enabling organizations to collaborate without sharing sensitive raw data, this research provides a pathway to leverage distributed datasets for improved forecasting accuracy. Thus, essay 4 bridges the gap between technological advancement and organizational needs in competitive supply chains. Concludingly, this essay contributes to the broader aim by illustrating how ML systems can be designed and applied to unlock efficiency and resilience in supply chains.

5.5 Essay 5: Understanding the machine economy: combining findings from science and practice

In the fifth essay, we tackled the nascent phenomenon of the ME, which integrates emerging digital technologies such as AI, internet of things and blockchain to enable economically autonomous acting machines. Our primary result is the establishment of a unified conceptual framework derived through a literature review and qualitative interviews. In essay 5, we not only synthesized the fragmented academic and practical understandings but also developed a five-layer model delineating the core functionalities required for ME applications. Our proposed model abstracts from specific technologies by emphasizing functionalities like connectivity, decision-making, and transactions, as well as further introducing two additional aspects: the physical actuation and identities.

Through this research, we made several contributions important for the academic discourse and the organization's product innovation. Academically, we unified previously disparate conceptualizations of the ME, laying a foundational understanding for future studies. By abstracting the ME to a functional level, we expanded its scope beyond technological constraints, enabling richer exploration across disciplines. Practically, our findings equip organizations with a roadmap to develop competencies and readiness for the ME. Specifically, the five-layer model provides a strategic lens for designing ME applications, fostering innovation, and ensuring alignment with evolving technological ecosystems.

In alignment with our RG to understand the path toward the ME, essay 5 bridges the gap between theory and practice. By presenting a robust, empirically grounded framework, we contribute significantly to the overarching aim of empowering organizations for the emerging ME. The essay sheds light on the ME and provides actionable insights to navigate its complexities, marking a step forward in addressing our RG.

5.6 Essay 6: Forecasting the emerging machine economy: toward a maturity model

In the sixth essay, we deliver a contribution to the overarching aim of enabling organizations to prepare for the emerging ME. In this essay, we developed the Machine Economy Entities Maturity Model (MEEMM), a comprehensive maturity model designed to assess and guide the progression of entities in the ME. The MEEMM encompasses six key dimensions – physical, connectivity, smartness, identity, interaction, and business – further divided into eleven sub-dimensions, with maturity levels ranging across five distinct stages for each sub-dimension. Our research culminated in the creation of the MEEMM, which provides a structured approach to evaluate and improve ME entities. Through an iterative design process involving literature review, industry interviews, and expert feedback, we constructed a model that integrates physical, informational, and organizational dimensions essential for ME entities. The MEEMM was applied to a real-world use case, Waymo's robotaxis, demonstrating its applicability and highlighting specific development paths for advancing their ME readiness.

Essay 6 contributes significantly to academic and practical domains by bridging conceptual insights and technical implementations within the ME. Academically, it extends the body of knowledge by offering a unified, capability-based model that addresses the maturity of ME entities comprehensively. This positions our work as a prescriptive tool that fosters dialogue and convergence among independent research streams on autonomy, connectivity, and interaction in economic contexts. Furthermore, the MEEMM serves as a vision-sharpening instrument, enabling practitioners to navigate strategic challenges and define development trajectories for their entities. Practically, the MEEMM provides a roadmap for organizations to mature their products and systems, making them suitable for the ME. It supports policymakers by offering a structured framework to anticipate regulatory requirements and prepare the STS for technological advancements. Additionally, the model underpins the derivation of innovative business models that align with ME paradigms, aiding decision-makers in crafting resilient and forward-thinking strategies.

In order to extend our insights on the ME, essay 6 directly builds upon the previous essay. This essay articulates a clear pathway toward the vision of the ME. The MEEMM offers actionable insights and practical tools to support the transition from conceptual understanding to operational readiness within organizations and their products. By delineating the capabilities required for participation in the ME, the essay ensures that both academia and practice are equipped to address the complexities of this transformative phenomenon. This foundational work establishes a basis for future exploration and innovation, advancing the overarching aim of enabling organizations for the emerging ME.

6 Discussion and conclusion

This section discusses and concludes the thesis' introduction. In section 6.1, I summarize the thesis and all contained essays. In section 6.2, I discuss the theoretical as well as the practical contribution. In section 6.3, I subsume the overall limitations of my research. In section 6.4, I give an outlook on future research opportunities.

6.1 Summary

Coming from the overall research aim to guide organizations toward the ME by improving AI development, I derived three RGs in this thesis. First, I address on the interplay of the social and technical system and try to enable organizations to manage AI development resources more efficiently. Second, I focus on improving the technical system to enable organizations to mitigate AI's data scarcity issue through DML. Third, I give a unified outlook from the social and the technical system's perspective on the ME, enabling organizations to understand the path toward the ME. In the essays, I employed various methodologies strengthening my results and insights. Methodologically, the essays mainly rely on DSR (Peffers et al., 2007), interviews (Myers and Newman, 2007), and the established maturity model methodology (Becker et al., 2009).

Essay 1 addresses *RG1* by proposing a resource portfolio on the development of AI. Additionally, the essay outlines the effects of investments in the various resource on the ML lifecycle. One of the resources discussed in essay 1 is the need of data for developing AI, the focus of *RG2*. Essay 2 takes a look at the research on using PETs to exploit distributed data sources without sharing the raw data. Further, this essay derives a research agenda on how to advance PETs for AI development from an IS point of view. Based on essay 2's findings, essay 3 and 4 implement technical artifacts using DML techniques to address common IS issues like business process management and mitigating bullwhip effect. After enabling organizations to better exploit AI, *RG3* now focuses on the emerging ME. Thus, essays 5 and 6 state the vision of the ME more precisely. The ME is a concept enabled through, the advances in AI development. It describes the emerging integration of autonomous machines in economic transactions and value creation. While essay 5 outlines a common understanding of the ME in the form of the 5-layer model, essay 6 proposes the MEEMM that helps organizations to advance their products and services to be ready for the ME.

6.2 Contribution to theory and implications for practice

Essay 1 assists organizations in exploiting AI effectively. The presented research adopts a resource portfolio perspective on AI development. By examining the interactions between different resources within the ML lifecycle, this essay provides foundational insights that bridge the gap between IS research and technical research. It explores how various resources, such as data, technology, and human expertise, interact and affect the ML lifecycle. This work lays the foundation for future research by bridging existing gaps between IS and technical IS research. It contributes to the literature by analyzing resource portfolios and their effects on AI development, offering a novel perspective that integrates organizational resources with technical advancements in AI. From a practical standpoint, our research guides organizations on effective resource allocation to improve AI development. It offers actionable insight not only for current AI projects but also for upcoming initiatives, enabling organizations to optimize resource allocation and enhance their AI capabilities.

As previously outlined, data scarcity poses a significant challenge in AI development. Essays 2, 3, and 4 address this issue by exploring PETs for AI from an IS perspective as a solution to data scarcity. These studies involve federating existing prescriptive process monitoring approaches and introducing a new split learning approach to effectively utilize distributed data. Bridging the gap from technical research to IS research, essay 2 proposes a research agenda to unveil the potential of PETs to IS. By introducing the technical DML approaches to address issues in other research domains, such as energy, it expands the applicability of advanced AI techniques across various sectors. Practically, the research presents two artifacts that enable organizations to overcome data scarcity. These artifacts provide tangible solutions for utilizing distributed data while maintaining privacy, thereby facilitating more robust AI development in data-constrained environments.

To comprehend and facilitate the transition toward the ME, essays 5 and 6 aim to develop a better understanding of the concept and illustrate the road toward the ME's realization. The essays contribute to research by establishing a common understanding of the ME within the academic community. By clarifying the concept, they provide a solid foundation for future research and development in this emerging field. On a practical level, essay 6 offers an innovation tool that enables organizations to enhance existing products and services or develop new ones tailored for the ME. Additionally, it provides policymakers with early insights into the manifestation of the ME, allowing them to prevent potential abuse and monopolies proactively.

The relevance of this research lies in its holistic approach to advancing AI development for the ME. By addressing organizational resource allocation, overcoming data scarcity, and clarifying the ME concept, the thesis provides valuable contributions to both academia and practice. The presented research contributes to enabling organizations to use AI (*RG1* and *RG2*) as well as it sheds light on the emerging machine economy (*RG3*) enabled by AI. It not only enriches academic discourse by bridging gaps between disciplines but also equips practitioners and policymakers with the tools and understanding necessary to navigate and shape the future of effectively developing AI and successfully creating the ME. This work empowers organizations to innovate and adapt in a rapidly evolving technological landscape, ensuring they remain competitive and responsible contributors to the ME.

6.3 Limitations

While this thesis advances the understanding and development of AI to enable the ME, several limitations must be acknowledged. These limitations arise from the rapid evolution of AI technologies, the specific focus areas of the research, as well as the challenges associated with translating theoretical models into practical applications.

A significant limitation under *RG1* is the rapid pace of advancements in AI technologies, such as generative AI (Gatla et al., 2024). These developments may either diminish the necessity for certain resources identified in this research or introduce new resources that were not previously considered. As AI technology evolves, the resource portfolio perspective and the associated effects between resources outlined in this thesis require reevaluation to remain relevant and effective for organizations aiming to fully exploit AI.

The research focusing on *RG2* predominantly centers on supervised learning methodologies. While supervised learning is the most common approach in AI (Jordan and Mitchell, 2015; Kühl et al., 2022), this narrow focus means that the findings may not be fully transferable to other learning paradigms like unsupervised or reinforcement learning. The reliance on supervised learning and the limited consideration of synthetic data constrain the generalizability of the proposed solutions across the broader spectrum of AI applications. Conclusively, the proposed software artifacts solely demonstrate the technologies' potential. While the thesis provides theoretical foundations and prototype-based research, there is a gap in translating these prototypes into practical, scalable solutions within industry settings. The proposed artifacts heavily rely on constraints that cannot be met in real-world implementations. The effectiveness of the proposed models and artifacts in real-world applications remains to be validated. Future research should focus on the practical implementation of these solutions, assessing their impact and adaptability in organizational contexts to bridge the gap between theory and practice.

The thesis's exploration of the ME (*RG3*) primarily emphasizes advancements in AI as the enabling factor. However, the ME also relies on advances in other emerging technologies and new developments in machine interactions (Jöhnk, Albrecht, et al., 2021). These developments are recognized but outside the scope of this thesis. Further, while this thesis is limited to existing use cases, future research will benefit from emerging new use cases. As new applications and scenarios arise, research should aim to understand their implications for technology development.

Recognizing these limitations is essential for contextualizing the contributions of this thesis and guiding future research, which will be subsequently discussed. Addressing the rapid evolution of AI technology, incorporating developments in other enabling technologies, and emphasizing practical implementation will be relevant steps toward enabling organizations to fully exploit the potential of AI and the ME.

6.4 Future research

Building upon the findings of this thesis, several avenues for future research emerge to further enhance the exploitation of AI as well as enable and participate in the ME. Besides addressing the thesis' previously mentioned limitations, this section outlines future research endeavors. Addressing these opportunities will help organizations keep up with technological advancements, overcome persistent challenges, and contribute to the evolving landscape of AI and autonomous systems.

While our research focused on the portfolio-view of AI development, future research could investigate individual resources. Exploring the success factors of strategic investments in specific resources, like data augmentation tools, complements our proposed resource portfolio. Research could explore what factors make specific tools effective and how they can be optimized for varying needs.

Exploring the concepts of coopetition and compensation mechanisms between organizations can offer insights into how organizations can collaborate and share data while maintaining competitive advantages (Gnyawali and Charleton, 2018). Research could examine models of cooperative competition where organizations jointly contribute to and benefit from shared AI resources. Future research can take up existing approaches from game theory, such as the envy-free equilibrium (Blum et al., 2021). Moreover, alternative approaches to address data scarcity, such as the Gaia-X initiative, present further research opportunities. Comparing different approaches helps to identify the most efficient and secure methods for collaborative utilization of confidential data. Guiding decision-makers in choosing the appropriate approach for their specific context will further mitigate the data scarcity issue.

While the thesis focuses on the entities within the ME, future research can address the governmental requirements for the ME. The cooperation and interaction of machines with humans and other machines demands sovereign functions. This includes aspects like standardized transaction mechanisms between machines and regulatory frameworks, which are crucial for the practical realization of the ME. Which functions are relevant and how they can be implemented is open to future research.

Giving a broader perspective, there is a lack of research on aspects of the ME, such as governance and liability. As machines become more autonomous and engage in economic transactions, establishing clear governance structures is a necessity to ensure efficient operation. Future studies should explore frameworks for machine interaction governance, legal liability in cases of malfunction or misconduct, and the development of policies that balance innovation with protection against abuse and monopolies. Interdisciplinary approaches combining legal studies, ethics, economics, and technology will be crucial in addressing these complex challenges.

Keeping IS research in focus, further research opportunities exist in examining how the imminent blurring of the social and technical systems affects existing knowledge and IS theories. Due to recent advances in AI technology, the demarcation between social and technical systems might become indistinct. This development can be anticipated by investigating how the demarcation must be adjusted and how IS theories are impacted by this shift. Alternatively, research might investigate how the technologies can be integrated while maintaining the distinction between both systems.

Future research opportunities will enable the advancement of AI as well as the successful and democratized realization of the ME. By keeping up with technological developments, rolling out solutions to data scarcity, expanding the focus to include other enabling technologies, as well as addressing governance and liability issues, researchers can contribute to create an efficient, ethical, and democratized ME. This proactive approach will equip organizations, policymakers, and society at large to navigate the rapidly evolving technological landscape and harness the full potential of AI and autonomous systems.

7 References

Ågerfalk, Pär J (2020). “Artificial intelligence as digital agency”. *European Journal of Information Systems* 29.1, pp. 1–8.

Ågerfalk, Pär J, Kieran Conboy, and Michael D Myers (2020). *Information systems in the age of pandemics: COVID-19 and beyond*.

Agrawal, Ajay, Joshua Gans, and Avi Goldfarb (2018). *Prediction machines*. Boston, MA: Harvard Business Review Press.

Agrawal, Pulkit, Rajat Arya, Aanchal Bindal, Sandeep Bhatia, Anupriya Gagneja, Joseph Godlewski, Yucheng Low, Timothy Muss, Mudit Manu Paliwal, Sethu Raman, Vishrut Shah, Bochao Shen, Laura Sugden, Kaiyu Zhao, and Ming-Chuan Wu (2019). “Data Platform for Machine Learning”. In: *Proceedings of the 2019 International Conference on Management of Data*. SIGMOD ’19. New York, NY, USA: Association for Computing Machinery, pp. 1803–1816. ISBN: 9781450356435. DOI: 10.1145/3299869.3314050.

Akhtar, Mohd Majid, Danish Raza Rizvi, Mohd Abdul Ahad, Salil S. Kanhere, Mohammad Amjad, and Giuseppe Coviello (2021). “Efficient Data Communication Using Distributed Ledger Technology and IOTA-Enabled Internet of Things for a Future Machine-to-Machine Economy”. *Sensors* 21.13. DOI: 10.3390/s21134354.

Alavi, Maryam, Dorothy E. Leidner, and Reza Mousavi (2024). “Knowledge Management Perspective of Generative Artificial Intelligence”. *Journal of the Association for Information Systems* 25.1, pp. 1–12. ISSN: 1536-9323. DOI: 10.17705/1jais.00859.

Albrecht, Tobias, Robert Keller, Dominik Rebholz, and Maximilian Röglinger (2024). “Fake it till you make it: Synthetic data for emerging carsharing programs”. *Transportation Research Part D: Transport and Environment* 127, p. 104067. ISSN: 1361-9209. DOI: 10.1016/j.trd.2024.104067.

Alromih, Arwa, John A. Clark, and Prosanta Gope (2022). “Privacy-Aware Split Learning Based Energy Theft Detection for Smart Grids”. In: *Information and Communications Security*. Ed. by Cristina Alcaraz, Liqun Chen, Shujun Li, and Pierangela Samarati. Cham: Springer International Publishing, pp. 281–300. ISBN: 978-3-031-15777-6.

Alter, Steven (2020). “Making Sense of Smartness in the Context of Smart Devices and Smart Systems”. *Information Systems Frontiers* 22.2, pp. 381–393. ISSN: 1572-9419. DOI: 10.1007/s10796-019-09919-9.

Amershi, Saleema, Andrew Begel, Christian Bird, Robert DeLine, Harald Gall, Ece Kamar, Nachiappan Nagappan, Besmira Nushi, and Thomas Zimmermann (2019). “Software Engineering for Machine Learning: A Case Study”. In: *Proceedings of the 41st International Conference on*

Software Engineering: Software Engineering in Practice. Montreal, Canada: IEEE, pp. 291–300. DOI: 10.1109/ICSE-SEIP.2019.00042.

Aral, Sinan, Chrysanthos Dellarocas, and David Godes (2013). "Introduction to the Special Issue – Social Media and Business Transformation: A Framework for Research". *Information Systems Research* 24.1, pp. 3–13. ISSN: 1047-7047. DOI: 10.1287/isre.1120.0470.

Arifovic, Jasmina, Xue-zhong He, and Lijian Wei (2022). "Machine learning and speed in high-frequency trading". *Journal of Economic Dynamics and Control* 139, p. 104438. ISSN: 0165-1889. DOI: 10.1016/j.jedc.2022.104438.

Arnott, David (2006). "Cognitive biases and decision support systems development: a design science approach". *Information Systems Journal* 16.1, pp. 55–78. DOI: https://doi.org/10.1111/j.1365-2575.2006.00208.x.

Arnott, David and Graham Pervan (2005). "A critical analysis of decision support systems research". *Journal of information technology* 20.2, pp. 67–87.

Arthur, W. Brian (2007). "The structure of invention". *Research Policy* 36.2, pp. 274–287. ISSN: 0048-7333. DOI: https://doi.org/10.1016/j.respol.2006.11.005.

Ashmore, Rob, Radu Calinescu, and Colin Paterson (2021). "Assuring the Machine Learning Lifecycle: Desiderata, Methods, and Challenges". *ACM Computing Surveys* 54.5, pp. 1–39.

Baier, Marie-Sophie, Stephan Berger, Thomas Kreuzer, Anna M. Oberländer, and Maximilian Röglinger (2023). "What Makes Digital Technology? A Categorization Based on Purpose". *Communications of the Association for Information Systems* 52, pp. 332–384. DOI: 10.17705/1CAIS.05215.

Baiyere, Abayomi, Hannu Salmela, and Tommi Tapanainen (2020). "Digital transformation and the new logics of business process management". *European Journal of Information Systems* 29.3, pp. 238–259. ISSN: 0960-085X. DOI: 10.1080/0960085X.2020.1718007.

Barney, Jay (1991). "Firm Resources and Sustained Competitive Advantage". *Journal of Management* 17.1, pp. 99–120. ISSN: 01492063.

Becker, Jörg, Ralf Knackstedt, and Jens Pöppelbuß (2009). "Developing Maturity Models for IT Management". *Business & Information Systems Engineering* 1.3, pp. 213–222. ISSN: 1867-0202. DOI: 10.1007/s12599-009-0044-5.

Berente, Nicholas, Bin Gu, Jan Recker, and Radhika Santhanam (2021). "Managing artificial intelligence." *MIS quarterly* 45.3.

Bharadwaj, Anandhi S. (2000). "A resource-based perspective on information technology capability and firm performance: an empirical investigation". *MIS Quarterly*, pp. 169–196.

Blum, Avrim, Haghtalab Nika, Richard Lanas Phillips, and Shao Han (2021). "One for One, or All for All: Equilibria and Optimality of Collaboration in Federated Learning". *International Conference on Machine Learning*, pp. 1005–1014. ISSN: 2640-3498.

Bonawitz, Keith (2019). “Towards federated learning at scale: Syste m design”. *arXiv preprint arXiv:1902.01046*.

Bostrom, Robert P. and J. Stephen Heinen (1977a). “MIS Problems and Failures: A Socio-Technical Perspective, Part II: The Application of Socio-Technical Theory”. *MIS Quarterly* 1.4, p. 11. ISSN: 0276-7783. DOI: `10.2307/249019`.

Bostrom, Robert P. and J. Stephen Heinen (1977b). “MIS Problems and Failures: A Socio-Technical Perspective. Part I: The Causes”. *MIS Quarterly* 1.3, p. 17. ISSN: 0276-7783. DOI: `10.2307/248710`.

Brik, Bouziane and Adlen Ksentini (2020). “On Predicting Service-oriented Network Slices Performances in 5G: A Federated Learning Approach”. In: *2020 IEEE 45th Conference on Local Computer Networks (LCN)*. IEEE, pp. 164–171. ISBN: 978-1-7281-7158-6. DOI: `10.1109/LCN48667.2020.9314849`.

Campesato, Oswald (2020). *Artificial Intelligence, Machine Learning, and Deep Learning*. Berlin, Boston: Mercury Learning and Information. ISBN: 9781683924654. DOI: `doi:10.1515/9781683924654`.

Chatterjee, Sutirtha, Suprateek Sarker, Michael J. Lee, Xiao Xiao, and Amany Elbanna (2020). “A possible conceptualization of the information systems (<scp>IS</scp>) artifact: A general systems theory perspective1”. *Information Systems Journal* 31.4, pp. 550–578. ISSN: 1365-2575. DOI: `10.1111/isj.12320`.

Chen, Frank, Zvi Drezner, Jennifer K. Ryan, and David Simchi-Levi (2000). “Quantifying the Bullwhip Effect in a Simple Supply Chain: The Impact of Forecasting, Lead Times, and Information”. *Management Science* 46.3, pp. 436–443. ISSN: 0025-1909. DOI: `10.1287/mnsc.46.3.436.12069`.

Corbin, Juliet M. and Anselm Strauss (1990). “Grounded theory research: Procedures, canons, and evaluative criteria”. *Qualitative Sociology* 13.1, pp. 3–21. ISSN: 1573-7837. DOI: `10.1007/BF00988593`.

Dally, William J., C. Thomas Gray, John Poulton, Brucek Khailany, John Wilson, and Larry Dennison (2018). “Hardware-Enabled Artificial Intelligence”. In: *2018 IEEE Symposium on VLSI Circuits*. IEEE, pp. 3–6. DOI: `10.1109/vlsic.2018.8502368`.

Dao, Tri, Albert Gu, Alexander Ratner, Virginia Smith, Chris De Sa, and Christopher Re (2019). “A Kernel Theory of Modern Data Augmentation”. In: *Proceedings of the 36th International Conference on Machine Learning*. Ed. by Kamalika Chaudhuri and Ruslan Salakhutdinov. Vol. 97. Proceedings of Machine Learning Research. PMLR, pp. 1528–1537.

Duda, Sebastian, Tobias Guggenberger, Domenique Zipperling, and Niklas Kühl (n.D.). “Designing Effective Collaborative Learning Systems: Demand Forecasting in Supply Chains Using Distributed Data”. *European Journal of Information Systems*.

Duda, Sebastian, Peter Hofmann, Nils Urbach, Fabiane Völter, and Amelie Zwickel (2024). "The Impact of Resource Allocation on the Machine Learning Lifecycle: Bridging the Gap between Software Engineering and Management". *Business & Information Systems Engineering* 66.2, pp. 203–219.

Duda, Sebastian, Marc Principato, Tobias Guggenberger, and Nils Urbach (n.D.). "Enabling Privacy and Collaboration: The Role of Privacy Enhancing Technologies in the Future of Artificial Intelligence". *Technological Forecasting and Social Change*.

Duda, Sebastian, Jens-Christian Stoetzer, Tobias Guggenberger, and Nils Urbach (2024). "Understanding the Machine Economy: Combining Findings from Science and Practice". *International Journal of Innovation and Technology Management* 21.04. ISSN: 1793-6950. DOI: 10.1142/s0219877024500342.

Dumas, Marlon, Marcello La Rosa, Jan Mendling, and Hajo A. Reijers (2018). *Fundamentals of Business Process Management*. Berlin, Heidelberg: Springer Berlin Heidelberg. ISBN: 978-3-662-56508-7. DOI: 10.1007/978-3-662-56509-4.

Eijnatten, Frans M van (2013). "Developments in socio-technical systems design (STSD)". In: *A handbook of work and organizational psychology*. Psychology Press, pp. 61–88.

Epley, Nicholas, Adam Waytz, and John T Cacioppo (2007). "On seeing human: a three-factor theory of anthropomorphism." *Psychological review* 114.4, p. 864.

Fahrenkrog-Petersen, Stephan A., Niek Tax, Irene Teinemaa, Marlon Dumas, Massimiliano de Leoni, Fabrizio Maria Maggi, and Matthias Weidlich (2022). "Fire now, fire later: alarm-based systems for prescriptive process monitoring". *Knowledge and Information Systems* 64.2, pp. 559–587. ISSN: 0219-1377. DOI: 10.1007/s10115-021-01633-w.

Forrester, Jay Wright (1961). *Industrial dynamics*. Portland, Oregon and Cambridge, Massachusetts: Productivity Press and M.I.T. Press Massachusetts Institute of Technology. ISBN: 0915299887.

Furman, Jason and Robert Seamans (2019). "AI and the Economy". *Innovation policy and the economy* 19.1, pp. 161–191.

Gao, Yunfan, Dong Han, Haofen Wang, Maohong Zhang, Fangjie Hou, Dongqing Yu, and Yun Xiong (2022). "GeoGTI: Towards a General, Transferable and Interpretable Site Recommendation". In: *Web Information Systems and Applications*. Springer International Publishing, pp. 559–571. ISBN: 9783031203091. DOI: 10.1007/978-3-031-20309-1_49.

Gatla, Ranjith Kumar, Anitha Gatla, Patti Sridhar, D. Kumar, and D. S. M. Rao (2024). "Advancements in Generative AI: Exploring Fundamentals and Evolution". *2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC)*, pp. 1–5. DOI: 10.1109/ICECCC61767.2024.10594003.

Gnyawali, Devi R. and Tadhg Ryan Charleton (2018). "Nuances in the Interplay of Competition and Cooperation: Towards a Theory of Coopetition". *Journal of Management* 44.7, pp. 2511–2534. ISSN: 0149-2063. DOI: 10.1177/0149206318788945.

Gomes, Carla et al. (2019). "Computational sustainability". *Communications of the ACM* 62.9, pp. 56–65. ISSN: 0001-0782. DOI: 10.1145/3339399.

Gramlich, Vincent, Tobias Guggenberger, Marc Principato, Benjamin Schellinger, and Nils Urbach (2023). "A multivocal literature review of decentralized finance: Current knowledge and future research avenues". *Electronic Markets* 33.1. ISSN: 1019-6781. DOI: 10.1007/s12525-023-00637-4.

Grant, Robert (1991). "The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation". *California Management Review* 33.3, pp. 114–135. ISSN: 0008-1256. DOI: 10.2307/41166664.

Gregor, Shirley and Alan R. Hevner (2013). "Positioning and Presenting Design Science Research for Maximum Impact". *MIS Quarterly* 37.2, pp. 337–355. ISSN: 02767783.

Guggenberger, Tobias, Jannik Lockl, Maximilian Röglinger, Vincent Schlatt, Johannes Sedlmeir, Jens-Christian Stoetzer, Nils Urbach, and Fabiane Völter (2021). "Emerging Digital Technologies to Combat Future Crises: Learnings From COVID-19 to be Prepared for the Future". *International Journal of Innovation and Technology Management* 18.04. ISSN: 1793-6950. DOI: 10.1142/s0219877021400022.

Gupta, Manjul and Joey F. George (2016). "Toward the development of a big data analytics capability". *Information & Management* 53.8, pp. 1049–1064. ISSN: 03787206. DOI: 10.1016/j.im.2016.07.004.

Hard, Andrew, Kanishka Rao, Rajiv Mathews, Swaroop Ramaswamy, Françoise Beaufays, Sean Augenstein, Hubert Eichner, Chloé Kiddon, and Daniel Ramage (2018). *Federated Learning for Mobile Keyboard Prediction*. DOI: 10.48550/arXiv.1811.03604.

Hartwich, Eduard, Alexander Rieger, Johannes Sedlmeir, Dominik Jurek, and Gilbert Fridgen (2023). "Machine economies". *Electronic Markets* 33.1. ISSN: 1019-6781. DOI: 10.1007/s12525-023-00649-0.

Herbst, Philip Gunter (1976). *Socio-Technical Design: Strategies in Multidisciplinary Research*. Tavistock Publications.

Herwix, Alexander and Amir Haj-Bolouri (2021). "Revisiting the Problem of The Problem : An Ontology and Framework for Problem Assessment in is Research". In: *European Conference on Information Systems (ECIS). Human value crisis in a digitized world : ECIS Proceedings*. ISBN: 978-1-7336325-6-0.

Hirt, Robin and Niklas Kühl (2018). "Cognition in the era of smart service systems: inter-organizational analytics through meta and transfer learning". In: *ICIS 2018 Proceedings*.

Hirt, Robin, Niklas Kühl, Dominik Martin, and Gerhard Satzger (2023). “Enabling inter-organizational analytics in business networks through meta machine learning”. *Information Technology and Management*. ISSN: 1573-7667. DOI: 10.1007/s10799-023-00399-7 .

Hollebeek, Linda D., David E. Sprott, and Michael K. Brady (2021). “Rise of the Machines? Customer Engagement in Automated Service Interactions”. *Journal of Service Research* 24.1, pp. 3–8. ISSN: 1094-6705. DOI: 10.1177/1094670520975110.

Hunke, Fabian, Daniel Heinz, and Gerhard Satzger (2022). “Creating customer value from data: foundations and archetypes of analytics-based services”. *Electronic Markets*, pp. 1–19.

Jain, Hemant, Balaji Padmanabhan, Paul A. Pavlou, and T. S. Raghu (2021). “Editorial for the Special Section on Humans, Algorithms, and Augmented Intelligence: The Future of Work, Organizations, and Society”. *Information Systems Research* 32.3, pp. 675–687. ISSN: 1047-7047. DOI: 10.1287/isre.2021.1046.

Jin, David, Niclas Kannengießer, Sascha Rank, and Ali Sunyaev (2024). *Collaborative Distributed Machine Learning*. arXiv: 2309.16584.

Jöhnk, Jan, Tobias Albrecht, Laurin Arnold, Tobias Guggenberger, Luis Lämmermann, André Schweizer, and Nils Urbach (2021). “The Rise of the Machines: Conceptualizing the Machine Economy.” In: *PACIS*, p. 54.

Jöhnk, Jan, Malte Weißert, and Katrin Wyrtki (2021). *Ready or Not, AI Comes – An Interview Study of Organizational AI Readiness Factors*. DOI: 10.1007/s12599-020-00676-7.

Jordan, Michael. I. and Tom Mitchell (2015). “Machine learning: Trends, perspectives, and prospects”. *Science (New York, N.Y.)* 349.6245, pp. 255–260. DOI: 10.1126/science.aaa8415.

Karnebogen, Philip, Can Kaymakci, Lukas Willburger, Björn Häckel, and Alexander Sauer (2023). “Structuring Federated Learning Applications — a Literature Analysis and Taxonomy”.

Khan, Asjad, Hung Le, Kien Do, Truyen Tran, Aditya Ghose, Hoa Dam, and Renuka Sindhgatta (2021). “DeepProcess: Supporting Business Process Execution Using a MANN-Based Recommender System”. In: *Service-Oriented Computing*. Ed. by Hakim Hacid, Odej Kao, Massimo Mecella, Naouel Moha, and Hye-young Paik. Vol. 13121. Lecture Notes in Computer Science. Cham: Springer International Publishing, pp. 19–33. ISBN: 978-3-030-91430-1. DOI: 10.1007/978-3-030-91431-8_2.

Kitchenham, Barbara and Stuart Charters (2007). “Guidelines for performing Systematic Literature Reviews in Software Engineering”. 2.

Konečnỳ, Jakub, H Brendan McMahan, Daniel Ramage, and Peter Richtárik (2016). “Federated optimization: Distributed machine learning for on-device intelligence”. *arXiv preprint arXiv:1610.02527*.

Konečný, Jakub, H. Brendan McMahan, Felix X. Yu, Peter Richtárik, Ananda Theertha Suresh, and Dave Bacon (2017). *Federated Learning: Strategies for Improving Communication Efficiency*. arXiv: 1610.05492.

Königs, Helge (2019). *The next big thing: Machine-to-Machine Economy: How and why we're teaching trucks how to pay*.

Koza, John R., Forrest H. Bennett, David Andre, and Martin A. Keane (1996). "Automated design of both the topology and sizing of analog electrical circuits using genetic programming". *Artificial intelligence in design'96*, pp. 151–170.

Kreuzer, Thomas, Maximilian Röglinger, and Lea Rupprecht (2020). "Customer-centric prioritization of process improvement projects". *Decision Support Systems* 133, p. 113286. ISSN: 01679236. DOI: 10.1016/j.dss.2020.113286.

Kubrak, Kateryna, Fredrik Milani, Alexander Nolte, and Marlon Dumas (2022). "Prescriptive process monitoring: Quo vadis?" *PeerJ. Computer science* 8, e1097. DOI: 10.7717/peerj-cs.1097.

Kühl, Niklas, Max Schemmer, Marc Goutier, and Gerhard Satzger (2022). "Artificial intelligence and machine learning". *Electronic Markets* 32.4, pp. 2235–2244. DOI: 10.1007/s12525-022-00598-0.

Lee, Hau L., V. Padmanabhan, and Seungjin Whang (1997). "Information Distortion in a Supply Chain: The Bullwhip Effect". *Management Science* 43.4, pp. 546–558. ISSN: 0025-1909. DOI: 10.1287/mnsc.43.4.546.

Lee, Junghee, Vish Krishnan, and Hyoduk Shin (2020). "Business Models for Technology-Intensive Supply Chains". *Management Science* 66.5, pp. 2120–2139. ISSN: 0025-1909. DOI: 10.1287/mnsc.2019.3306.

Lee, Sang M, David L Olson, and Silvana Trimi (2010). "Strategic innovation in the convergence era". *International Journal of Management and Enterprise Development* 9.1, pp. 1–12.

Leminen, Seppo, Mervi Rajahonka, Robert Wendelin, and Mika Westerlund (2020). "Industrial internet of things business models in the machine-to-machine context". *Industrial Marketing Management* 84, pp. 298–311. ISSN: 0019-8501. DOI: 10.1016/j.indmarman.2019.08.008.

Li, Li, Yuxi Fan, Mike Tse, and Kuo-Yi Lin (2020). "A review of applications in federated learning". *Computers & Industrial Engineering* 149, p. 106854. ISSN: 03608352. DOI: 10.1016/j.cie.2020.106854.

Li, Mengjun and Ayoung Suh (2021). "Machinelike or Humanlike? A Literature Review of Anthropomorphism in AI-Enabled Technology". In: *Proceedings of the 54th Hawaii International Conference on System Sciences*. Ed. by Tung Bui. Proceedings of the Annual Hawaii

International Conference on System Sciences. Hawaii International Conference on System Sciences. DOI: 10.24251/HICSS.2021.493.

Li, Qinbin, Zeyi Wen, Zhaomin Wu, Sixu Hu, Naibo Wang, Yuan Li, Xu Liu, and Bingsheng He (2021). “A survey on federated learning systems: Vision, hype and reality for data privacy and protection”. *IEEE Transactions on Knowledge and Data Engineering* 35.4, pp. 3347–3366. DOI: 10.1109/TKDE.2021.3124599.

Li, Shiyao, Yiqun Pan, Peng Xu, and Nan Zhang (2021). “A decentralized peer-to-peer control scheme for heating and cooling trading in distributed energy systems”. *Journal of Cleaner Production* 285, p. 124817. ISSN: 09596526. DOI: 10.1016/j.jclepro.2020.124817.

Liu, Ji, Jizhou Huang, Yang Zhou, Xuhong Li, Shilei Ji, Haoyi Xiong, and Dejing Dou (2022). “From distributed machine learning to federated learning: a survey”. *Knowledge and Information Systems* 64.4, pp. 885–917. ISSN: 0219-3116. DOI: 10.1007/s10115-022-01664-x.

Liu, Yi, Jiangtian Nie, Xuandi Li, Syed Hassan Ahmed, Wei Yang Bryan Lim, and Chunyan Miao (2021). “Federated Learning in the Sky: Aerial-Ground Air Quality Sensing Framework With UAV Swarms”. *IEEE Internet of Things Journal* 8.12, pp. 9827–9837. DOI: 10.1109/JIOT.2020.3021006.

Macías-Escrivá, Frank D., Rodolfo Haber, Raul del Toro, and Vicente Hernandez (2013). “Self-adaptive systems: A survey of current approaches, research challenges and applications”. *Expert Systems with Applications* 40.18, pp. 7267–7279. ISSN: 0957-4174. DOI: 10.1016/j.eswa.2013.07.033.

Maedche, Alexander, Shirley Gregor, Stefan Morana, and Jasper Feine (2019). “Conceptualization of the Problem Space in Design Science Research”. In: *Extending the Boundaries of Design Science Theory and Practice*. Springer International Publishing, pp. 18–31. ISBN: 9783030195045. DOI: 10.1007/978-3-030-19504-5_2.

Makarius, Erin E., Debmalya Mukherjee, Joseph D. Fox, and Alexa K. Fox (2020). “Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization”. *Journal of Business Research* 120, pp. 262–273. ISSN: 0148-2963. DOI: 10.1016/j.jbusres.2020.07.045.

March, Salvatore T. and Gerald F. Smith (1995). “Design and natural science research on information technology”. *Decision Support Systems* 15.4, pp. 251–266. ISSN: 01679236. DOI: 10.1016/0167-9236(94)00041-2.

McMahan, Brendan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y. Arcas (2017). “Communication-Efficient Learning of Deep Networks from Decentralized Data”. In: *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*. Ed.

by Aarti Singh and Jerry Zhu. Vol. 54. Proceedings of Machine Learning Research. PMLR, pp. 1273–1282.

Mercan, Suat, Ahmet Kurt, Kemal Akkaya, and Enes Erdin (2022). "Cryptocurrency Solutions to Enable Micropayments in Consumer IoT". *IEEE Consumer Electronics Magazine* 11.2, pp. 97–103. ISSN: 2162-2248. DOI: 10.1109/MCE.2021.3060720.

Mercedes Benz AG (2023). *In-car payment by using your fingerprint | Mercedes-Benz Mobility AG – mercedes-benz-mobility.com*.

Miehle, Daniel, Matthias M. Meyer, Andre Luckow, Bernd Bruegge, and Michael Essig (2019). "Toward a Decentralized Marketplace for Self-Maintaining Machines". In: *2019 IEEE International Conference on Blockchain (Blockchain)*. IEEE, pp. 431–438. ISBN: 978-1-7281-4693-5. DOI: 10.1109/Blockchain.2019.00066.

Mikalef, Patrick, Ilias O. Pappas, John Krogstie, and Michail Giannakos (2018). "Big data analytics capabilities: a systematic literature review and research agenda". *Information Systems and e-Business Management* 16.3, pp. 547–578. ISSN: 1617-9846. DOI: 10.1007/s10257-017-0362-y.

Mitchell, Tom M. (1997). *Machine Learning*. 1st ed. New York: McGraw-Hill. ISBN: 0070428077.

Moder, Linda, Sebastian Duda, Lukas Willburger, Roberto Kraus Caballero, Björn Häckel, Maximilian Röglinger, and Nils Urbach (n.D.). "Toward Data-Sovereign Prescriptive Process Monitoring: A Federated Learning Approach". In: *Proceedings of the 33rd European Conference on Information Systems 2025*.

Muhammad, Ghulam, Salman Alqahtani, and Abdullah Alelaiwi (2021). "Pandemic Management for Diseases Similar to COVID-19 Using Deep Learning and 5G Communications". *IEEE Network* 35.3, pp. 21–26. ISSN: 0890-8044. DOI: 10.1109/MNET.011.2000739.

Müller, Oliver, Iris Junglas, Jan vom Brocke, and Stefan Debortoli (2016). "Utilizing big data analytics for information systems research: challenges, promises and guidelines". *European Journal of Information Systems* 25.4, pp. 289–302. DOI: 10.1057/ejis.2016.2.

Mumford, Enid (2000). "A Socio-Technical Approach to Systems Design". *Requirements Engineering* 5.2, pp. 125–133. ISSN: 0947-3602. DOI: 10.1007/pl00010345.

Musso, Stefano, Guido Perboli, Mariangela Rosano, and Alessandro Manfredi (2019). "A Decentralized Marketplace for M2M Economy for Smart Cities". In: *2019 IEEE 28th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises*. IEEE, pp. 27–30. ISBN: 978-1-7281-0676-2. DOI: 10.1109/WETICE.2019.00014.

Myers, Michael D. and Michael Newman (2007). "The qualitative interview in IS research: Examining the craft". *Information and Organization* 17.1, pp. 2–26. ISSN: 14717727. DOI: 10.1016/j.infoandorg.2006.11.001.

Nguyen, Dinh C, Quoc-Viet Pham, Pubudu N. Pathirana, Ming Ding, Aruna Seneviratne, Zihuai Lin, Octavia Dobre, and Won-Joo Hwang (2023). "Federated Learning for Smart Healthcare: A Survey". *ACM Computing Surveys* 55.3. ISSN: 0360-0300. DOI: 10.1145/3501296.

Nuti, Giuseppe, Mahnoosh Mirghaemi, Philip Treleaven, and Chaiyakorn Yingsaeree (2011). "Algorithmic Trading". *Computer* 44.11, pp. 61–69. ISSN: 0018-9162. DOI: 10.1109/MC.2011.31.

Oosthuizen, Rudolph and Leon Pretorius (2014). "Modelling Methodology for Engineering of Complex Sociotechnical Systems". *INCOSE International Symposium* 24.s1, pp. 268–281. ISSN: 2334-5837. DOI: 10.1002/j.2334-5837.2014.00021.x.

Oosthuizen, Rudolph and Leon Pretorius (2016). "Assessing the Impact of New Technology on Complex Sociotechnical Systems". *South African Journal of Industrial Engineering* 27.2. ISSN: 2224-7890. DOI: 10.7166/27-2-1144.

Panarello, Alfonso, Nachiket Tapas, Giovanni Merlino, Francesco Longo, and Antonio Puliafito (2018). "Blockchain and IoT Integration: A Systematic Survey". *Sensors (Basel, Switzerland)* 18.8. DOI: 10.3390/s18082575.

Park, Gyunam and Wil van der Aalst (2022). "Action-oriented process mining: bridging the gap between insights and actions". *Progress in Artificial Intelligence*. ISSN: 2192-6352. DOI: 10.1007/s13748-022-00281-7.

Pasmore, William A (1988). "Designing effective organizations: The sociotechnical systems perspective".

Peffers, Ken, Tuure Tuunanen, Marcus A. Rothenberger, and Samir Chatterjee (2007). "A Design Science Research Methodology for Information Systems Research". *Journal of Management Information Systems* 24.3, pp. 45–77. ISSN: 0742-1222. DOI: 10.2753/MIS0742-1222240302.

Poirot, Maarten G., Praneeth Vepakomma, Ken Chang, Jayashree Kalpathy-Cramer, Rajiv Gupta, and Ramesh Raskar (2019). *Split Learning for collaborative deep learning in healthcare*. arXiv: 1912.12115.

Power, Daniel J., Dale Cyphert, and Roberta M. Roth (2019). "Analytics, bias, and evidence: the quest for rational decision making". *Journal of Decision Systems* 28.2, pp. 120–137. DOI: 10.1080/12460125.2019.1623534.

Risius, Marten and Kai Spohrer (2017). "A Blockchain Research Framework". *Business & Information Systems Engineering* 59.6, pp. 385–409. ISSN: 2363-7005. DOI: 10.1007/s12599-017-0506-0.

Röglinger, Maximilian and Jens Pöppelbuß (2011). "What makes a useful maturity model? : A framework for general design principles for maturity models and its demonstration in business process management". In: *Proceedings of the 19th European Conference on Information Systems (ECIS)*. Helsinki. ISBN: 978-952-60-3574-1.

Romanini, Daniele, Adam James Hall, Pavlos Papadopoulos, Tom Titcombe, Abbas Ismail, Tudor Cebere, Robert Sandmann, Robin Roehm, and Michael A Hoeh (2021). "PyVertical: A Vertical Federated Learning Framework for Multi-headed SplitNN". *arXiv preprint arXiv:2104.00489*.

Russell, Stuart and Peter Norvig (2016). *Artificial intelligence: A modern approach*. Third edition. Boston: Pearson. ISBN: 9781292153971.

Rzepka, Christine and Benedikt Berger (2018). "User interaction with AI-enabled systems: A systematic review of IS research". In: *Proceedings of the 39th International Conference on Information Systems (ICIS)*.

Schlecht, Laura, Sabrina Schneider, and Arne Buchwald (2020). "Creating Value Through Blockchain Technology: A Delphi Study". In: *Proceedings of the 28th European Conference on Information Systems*.

Schleiffer, Ralf (2005). "An intelligent agent model". *European Journal of Operational Research* 166.3, pp. 666–693. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2004.03.039.

Schuetz, Sebastian and Viswanath Venkatesh (2020). "The Rise of Human Machines: How Cognitive Computing Systems Challenge Assumptions of User-System Interaction". *Journal of the Association for Information Systems*, pp. 460–482. DOI: 10.17705/1jais.00608.

Schweizer, Andre, Patricia Knoll, Nils Urbach, Heiko Andreas von der Gracht, and Thomas Hardjono (2020). "To What Extent Will Blockchain Drive the Machine Economy? Perspectives From a Prospective Study". *IEEE Transactions on Engineering Management* 67.4, pp. 1169–1183. ISSN: 0018-9391. DOI: 10.1109/TEM.2020.2979286.

Shani, A.B. (Rami), Robert M. Grant, R. Krishnan, and Eric Thompson (1992). "Advanced Manufacturing Systems and Organizational Choice: Sociotechnical System Approach". *California Management Review* 34.4, pp. 91–111. ISSN: 2162-8564. DOI: 10.2307/41166705.

Shokri, Reza, Marco Stronati, Congzheng Song, and Vitaly Shmatikov (2017). "Membership inference attacks against machine learning models". In: *2017 IEEE symposium on security and privacy (SP)*. IEEE, pp. 3–18.

Sonnenberg, Christian and Jan vom Brocke (2012). "Evaluation Patterns for Design Science Research Artefacts". In: *Practical Aspects of Design Science*. Ed. by Markus Helfert and Brian Donnellan. Vol. 286. Communications in Computer and Information Science. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 71–83. ISBN: 978-3-642-33680-5. DOI: 10.1007/978-3-642-33681-2_7.

Soykan, Elif Ustundag, Leyli Karaçay, Ferhat Karakoç, and Emrah Tomur (2022). "A Survey and Guideline on Privacy Enhancing Technologies for Collaborative Machine Learning". *IEEE*

Access 10, pp. 97495–97519. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2022.3204037.

Stoetzer, Jens-Christian, Sebastian Duda, Florian Hawlitschek, Tobias Guggenberger, and Nils Urbach (n.D.). “Forecasting the Emerging Machine Economy: Toward a Maturity Model”. *Technological Forecasting and Social Change*.

Sykes, Tracy Ann, Viswanath Venkatesh, and Jonathan L. Johnson (2014). “Enterprise System Implementation and Employee Job Performance: Understanding the Role of Advice Networks”. *MIS Quarterly* 38.1, pp. 51–72. ISSN: 02767783, 21629730.

Taylor, Petroc (2024). *Data growth worldwide 2010-2028, Statista*. https://www.statista.com/statistics/871513/worldwide-data-created/. [Accessed 23-11-2024].

Thapa, Chandra, Pathum Chamikara Mahawaga Arachchige, Seyit Camtepe, and Lichao Sun (2022). “SplitFed: When Federated Learning Meets Split Learning”. *Proceedings of the AAAI Conference on Artificial Intelligence* 36.8, pp. 8485–8493. ISSN: 2159-5399. DOI: 10.1609/aaai.v36i8.20825.

Trist, E. L. and K. W. Bamforth (1951). “Some Social and Psychological Consequences of the Longwall Method of Coal-Getting: An Examination of the Psychological Situation and Defences of a Work Group in Relation to the Social Structure and Technological Content of the Work System”. *Human Relations* 4.1, pp. 3–38. ISSN: 1741-282X. DOI: 10.1177/001872675100400101.

Tun, Ye Lin, Kyi Thar, Chu Myaet Thwal, and Choong Seon Hong (2021). “Federated Learning based Energy Demand Prediction with Clustered Aggregation”. In: *2021 IEEE International Conference on Big Data and Smart Computing (BigComp)*. IEEE, pp. 164–167. ISBN: 978-1-7281-8924-6. DOI: 10.1109/BigComp51126.2021.00039.

Tuunanen, Tuure, Robert Winter, and Jan vom Brocke (2024). “Dealing with Complexity in Design Science Research: A Methodology Using Design Echelons”. *MIS Quarterly* 48.2, pp. 427–458. ISSN: 02767783. DOI: 10.25300/MISQ/2023/16700.

Urbach, Nils, Tobias Albrecht, Tobias Guggenberger, Jan Jöhnk, Laurin Arnold, Julia Gebert, Dennis Jelito, Luis Lämmermann, and Andreas Schweizer (2020). *The Advance of the Machines – Vision und Implikationen einer Machine Economy*.

Venable, John, Jan Pries-Heje, and Richard Baskerville (2016). “FEDS: a Framework for Evaluation in Design Science Research”. *European Journal of Information Systems* 25.1, pp. 77–89. ISSN: 0960-085X. DOI: 10.1057/ejis.2014.36.

Vepakomma, Praneeth, Otkrist Gupta, Tristan Swedish, and Ramesh Raskar (2018). *Split learning for health: Distributed deep learning without sharing raw patient data*. DOI: 10.48550/arXiv.1812.00564.

Verleysen, Michel and Damien François (2005). “The Curse of Dimensionality in Data Mining and Time Series Prediction”. In: *Computational Intelligence and Bioinspired Systems*. Ed. by Joan Cabestany, Alberto Prieto, and Francisco Sandoval. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 758–770. ISBN: 978-3-540-32106-4.

Verma, Pawan Kumar, Rajesh Verma, Arun Prakash, Ashish Agrawal, Kshirasagar Naik, Rajeev Tripathi, Maazen Alsabaan, Tarek Khalifa, Tamer Abdelkader, and Abdulhakim Abogharaf (2016). “Machine-to-Machine (M2M) communications: A survey”. *Journal of Network and Computer Applications* 66, pp. 83–105. ISSN: 1084-8045. DOI: 10.1016/j.jnca.2016.02.016.

Webster, Jane and Richard T. Watson (2002). “Analyzing the Past to Prepare for the Future: Writing a Literature Review”. *MIS Quarterly* 26.2, pp. xiii–xxiii. ISSN: 02767783.

Wen, Jie, Zhixia Zhang, Yang Lan, Zhihua Cui, Jianghui Cai, and Wensheng Zhang (2022). “A survey on federated learning: challenges and applications”. *International Journal of Machine Learning and Cybernetics* 14.2, pp. 513–535. ISSN: 1868-808X. DOI: 10.1007/s13042-022-01647-y.

Whang, Steven Euijong, Yuji Roh, Hwanjun Song, and Jae-Gil Lee (2021). “Data collection and quality challenges in deep learning: a data-centric AI perspective”. *The VLDB Journal* 32, pp. 791–813. DOI: 10.1007/s00778-022-00775-9.

Zhang, Xinqian, Ming Hu, Jun Xia, Tongquan Wei, Mingsong Chen, and Shiyan Hu (2021). “Efficient Federated Learning for Cloud-Based AIoT Applications”. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems* 40.11, pp. 2211–2223. ISSN: 0278-0070. DOI: 10.1109/TCAD.2020.3046665.

Zhu, Ligeng, Zhijian Liu, and Song Han (2019). “Deep Leakage from Gradients”. In: *Advances in Neural Information Processing Systems*. Ed. by H. Wallach, H. Larochelle, A. Beygelzimer, F. Alché-Buc, E. Fox, and R. Garnett. Vol. 32. Curran Associates, Inc.

Zhu, Xiaodan, Anh Ninh, Hui Zhao, and Zhenming Liu (2021). “Demand forecasting with supply-chain information and machine learning: Evidence in the pharmaceutical industry”. *Production and Operations Management* 30.9, pp. 3231–3252.

A Further publications during the dissertation

Christine van Stiphoudt, Sergio Potenciano Menci, Can Kaymakci, Simon Wenninger, Dennis Bauer, Sebastian Duda, Gilbert Fridgen, Alexander Sauer. (2025). The energy synchronization platform concept in the model region Augsburg to enable and streamline automated industrial demand response. Applied Energy. https://doi.org/10.2139/ssrn.4815433

Gramlich, V., Guggenberger, T., Principato, M., Schellinger, B., Duda, S., & Stoetzer, J. (2024). In Decentralized Finance Nobody Knows You Are a Dog. In Proceedings of the 57th Hawaii International Conference on System Sciences.
https://hdl.handle.net/10125/106932

Deppner, L., Duda, S., Guggenberger, T., Ketenedis, D., Kreuzer, T., Oberländer, A. M., & Rex, A. (2024). Erfolgsrezepte: Räume für Innovation gestalten.
https://doi.org/10.24406/publica-2783

---

van Stiphoudt, C., POTENCIANO MENCI, S., Kaymakci, C., Wenninger, S., Bauer, D., Duda, S., ... & Sauer, A. (2024). Energy Synchronization Platform Concept to Enable and Streamline Automated Industrial Demand Response. Energy Proceedings.
https://doi.org/10.46855/energy-proceedings-10990

Duda, S., Fischer-Brandies, L., Guggenberger, T., Häckel, B., Oberländer, A. M., Rex, A., ... & Volland, M. (2023). Lebensmittelindustrie 4.0.
https://doi.org/10.24406/publica-1039

Duda, S., Fabri, L., Kaymakci, C., Wenninger, S., & Sauer, A. (2023). Deriving Digital Energy Platform Archetypes for Manufacturing – A Data-Driven Clustering Approach. In Proceedings of the Conference on Production Systems and Logistics: CPSL 2023.
https://doi.org/10.15488/13424

Duda, S., Kaymakci, C., Köberlein, J., Wenninger, S., Haubner, T., Sauer, A., & Schilp, J. (2022). Structuring the Digital Energy Platform Jungle: Development of a Multi-Layer Taxonomy and Implications for Practice. In Proceedings of the Conference on Production Systems and Logistics: CPSL 2022.
https://doi.org/10.15488/12192

Buhl, H. U., Duda, S., Schott, P., Weibelzahl, M., Wenninger, S., Fridgen, G., ... & Lindner, M. (2021). Energieflexibilitätsdatenmodell der Energiesynchronisationsplattform: Teil der Reihe Diskussionspapiere V4 Konzept der Energiesynchronisationsplattform. sl.
https://doi.org/10.24406/IGCV-N-642370

B Author contribution statements

This section contains the author contribution statements of all essays. I submitted signed copies that declare the authors' individual contributions with this thesis.

B.1 Essay 1: Systematizing the effects of machine learning resources: a machine learning lifecycle perspective

The research paper "Systematizing the Effects of Machine Learning Resources: An ML Lifecycle Perspective" was co-authored by Sebastian Duda, Peter Hofmann, Nils Urbach, Fabiane Völter, and Amelie Zwickel. The co-authors contributed as follows:

Sebastian Duda (co-author) initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation, conducting and analysing the interviews, and developing the framework over all iterations. Further, he engaged in textual elaboration, especially in the introduction, theoretical background, method, results, discussion, and conclusion sections. He also participated in research discussions and provided feedback on the paper's content and structure. Thus, Sebastian Duda's co-authorship is reflected in the entire research project.

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

Nils Urbach (co-author) co-developed the research project. He provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript both over the course of the initial submission and the revision process.

Fabiane Völter (co-author) initiated and co-developed the research project. She contributed by developing the paper's theoretical foundation, conducting and analysing the interviews, and developing the framework over all iterations. Further, she engaged in textual elaboration, especially in the introduction, theoretical background, method, results, discussion, and conclusion sections. She also participated in research discussions and provided feedback on the paper's content and structure. Thus, Fabiane Völter's co-authorship is reflected in the entire research project.

Amelie Zwickel (co-author) contributed by developing the paper's theoretical foundation, conducting and analyzing the interviews, and developing the initial framework. Further, she engaged in textual elaboration, especially in the first draft of the manuscript. She also participated in research discussions. Thus, Amelie Zwickel's co-authorship is reflected in the entire research project.

B.2 Essay 2: Enabling privacy and collaboration: the role of privacy enhancing technologies in the future of artificial intelligence

The research paper "Enabling Privacy and Collaboration: The Role of Privacy Enhancing Technologies in the Future of Artificial Intelligence" was co-authored by Sebastian Duda, Tobias Guggenberger, Marc Principato, and Nils Urbach. The co-authors contributed as follows:

Sebastian Duda (co-author) initiated and co-developed the research project. He had a substantial role in conceptualizing the paper and curating the methodology. He contributed to investigation and data curation. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. Further, he took on project administration.

Marc Principato (co-author) initiated and co-developed the research project. He had a substantial role in conceptualizing the paper and curating the methodology. He contributed to investigation and data curation. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. Further, he took on project administration.

Tobias Guggenberger (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission.

Nils Urbach (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission.

B.3 Essay 3: Toward data-sovereign prescriptive process monitoring: a federated learning approach

The research paper "Toward Data-Sovereign Prescriptive Process Monitoring: A Federated Learning Approach" was co-authored by Linda Moder, Sebastian Duda, Lukas Willburger, Roberto Kraus Caballero, Björn Häckel, Maximilian Röglinger, and Nils Urbach. The co-authors contributed as follows:

Linda Moder (co-author) had a substantial role in conceptualizing the paper and designing the methodology. During the design, development, and application of the method and the corresponding software prototype, she contributed to the investigation and data curation. She was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. Further, she took on project administration.

Sebastian Duda (co-author) initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation, designing the methodology, as well as participating in implementing the artifact. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper.

Lukas Willburger (co-author) initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation, designing the methodology, as well as participating in implementing the artifact. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper.

Roberto Kraus Caballero (subordinate author) contributed by developing the paper's theoretical foundation and implementing the artifact in a lead role. He was responsible for designing the software architecture and generating the data for evaluating the artifact.

Björn Häckel (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission.

Maximilian Röglinger (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission.

Nils Urbach (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission.

B.4 Essay 4: Designing effective collaborative learning systems: demand forecasting in supply chains using distributed data

The research paper "Designing Effective Collaborative Learning Systems: Demand Forecasting in Supply Chains Using Distributed Data" was co-authored by Sebastian Duda, Tobias Guggenberger, Domenique Zipperling, and Niklas Kühl. The co-authors contributed as follows:

Sebastian Duda (co-author) initiated and co-developed the research project. He had a substantial role in conceptualizing the paper and designing the methodology. He contributed to investigation and data curation. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. Further, he took on project administration.

Tobias Guggenberger (co-author) initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation and designing the methodology. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper.

Domenique Zipperling (co-author) initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation, designing the software artifact. He contributed to collect data for the evaluation. He was further responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper.

Niklas Kühl (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission.

B.5 Essay 5: Understanding the machine economy: combining findings from science and practice

The research paper "Understanding the Machine Economy: Combining Findings from Science and Practice" was co-authored by Sebastian Duda, Jens-Christian Stoetzer, Tobias Guggenberger, and Nils Urbach. The co-authors contributed as follows:

Sebastian Duda (lead author) initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation and curating the methodological approach. Further, he was responsible for data collection. Jointly with the other authors, he developed and evaluated the artifact. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. He contributed as the lead author of the research paper.

Jens-Christian Stoetzer (subordinate author) initiated and co-developed the research project. He contributed to the paper's theoretical foundation. He contributed to the data collection. He participated in developing and evaluating the artifact. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. He contributed as subordinate author of the research paper.

Tobias Guggenberger (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission. He contributed as subordinate author of the research paper.

Nils Urbach (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission. He contributed as subordinate author of the research paper.

B.6 Essay 6: Forecasting the emerging machine economy: toward a maturity model

The research paper "Forecasting the Emerging Machine Economy: Toward a Maturity Model" was co-authored by Jens-Christian Stoetzer, Sebastian Duda, Florian Hawlitschek, Tobias Guggenberger, and Nils Urbach. The co-authors contributed as follows:

Jens-Christian Stoetzer (lead author) initiated and co-developed the research project. He contributed by developing the paper's theoretical foundation and curating the methodological approach. Further, he was responsible for data collection. Jointly with the other authors, he developed and evaluated the artifact. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. He contributed as the lead author of the research paper.

Sebastian Duda (subordinate author) initiated and co-developed the research project. He contributed to the paper's theoretical foundation. He contributed to the data collection. He participated in developing and evaluating the artifact. He was responsible for writing parts of the original draft and was involved in reviewing and editing the entire paper. He contributed as subordinate author of the research paper.

Florian Hawlitschek (subordinate author) provided mentorship and feedback on the paper's content and structure. He participated in developing and evaluating the artifact. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission. He contributed as subordinate author of the research paper.

Tobias Guggenberger (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission. He contributed as subordinate author of the research paper.

Nils Urbach (subordinate author) provided mentorship and feedback on the paper's content and structure. He also engaged in the textual elaboration with respect to reviewing and editing of the entire manuscript over the course of the initial submission. He contributed as subordinate author of the research paper.

Systematizing the Effects of Machine Learning Resources: An ML Lifecycle Perspective

Authors

Sebastian Duda, Peter Hofmann, Nils Urbach, Fabiane Völter, Amelie Zwickel

Abstract

The paper examines the increasing interest of organizations in leveraging Artificial Intelligence (AI) within their operations. AI presents a multitude of opportunities, but it also poses challenges, notably in the efficient development of AI applications. Despite significant financial investments, many organizations encounter persistent obstacles in AI development. This paper explores how the allocation of resources affects the Machine Learning (ML) lifecycle, seeking a deeper understanding of these challenges and offering potential solutions.

We develop a framework using the Design Science Research (DSR) paradigm (Peffers et al., 2007) to address the issues of inefficient resource allocation. The DSR paradigm helps build a structured approach to creating this framework, focusing on aligning resource availability with the technical and procedural needs of the ML lifecycle. The study builds on existing literature and expert insights, incorporating the Resource-Based View (Bharadwaj, 2000; Grant, 1991; Powell, 1992) as a theoretical lens to comprehend the strategic value and impact of various resources within the ML lifecycle.

Based on existing ML lifecycle models, particularly those by Amershi et al. (2019) and Ashmore et al. (2021), we identify 30 vital resources necessary for the successful development of AI applications. These resources play critical roles at various stages of the ML lifecycle, ranging from data acquisition and processing to model training

and deployment. The identification process underscores the diversity of resources and their intricate interdependencies, highlighting the need for strategic resource allocation to enhance the performance and outcomes of ML initiatives.

Furthermore, the paper discusses six distinct effects that investments in individual resources have on the ML lifecycle. These effects elucidate how resource allocation can either facilitate or hinder the progress of developing AI applications. We aim to provide an understanding of these impacts, helping organizations to make informed decisions about where to allocate their resources to achieve maximum efficiency and effectiveness in their AI endeavors.

In the discussion, the study acknowledges certain limitations, particularly in the evolving nature of ML practices and the rapid changes in technology and resource requirements that may affect the framework's long-term applicability. Moreover, the research is limited by the potential biases in expert feedback and the constraints of conducting a literature review that may not cover all relevant works. In conclusion, by integrating insights from software engineering and management disciplines, the paper offers a novel perspective on the strategic management of resources in the context of AI development. It emphasizes the importance of understanding not merely the existence of resources but their specific implications within the organizational and technological landscape, aiding organizations in navigating the complexities of AI application development.

Keywords

ML management, machine learning lifecycle, artificial intelligence, resource-based view, design science research

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References

Amershi, Saleema, Andrew Begel, Christian Bird, Robert DeLine, Harald Gall, Ece Kamar, Nachiappan Nagappan, Besmira Nushi, and Thomas Zimmermann (2019). "Software Engineering for Machine Learning: A Case Study". In: *Proceedings of the 41st International Conference on*

Software Engineering: Software Engineering in Practice. Montreal, Canada: IEEE, pp. 291–300. DOI: 10.1109/ICSE-SEIP.2019.00042.

Ashmore, Rob, Radu Calinescu, and Colin Paterson (2021). “Assuring the Machine Learning Lifecycle: Desiderata, Methods, and Challenges”. *ACM Computing Surveys* 54.5, pp. 1–39.

Bharadwaj, Anandhi S. (2000). “A resource-based perspective on information technology capability and firm performance: an empirical investigation”. *MIS Quarterly*, pp. 169–196.

Grant, Robert (1991). “The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation”. *California Management Review* 33.3, pp. 114–135. ISSN: 0008-1256. DOI: 10.2307/41166664.

Peffers, Ken, Tuure Tuunanen, Marcus A. Rothenberger, and Samir Chatterjee (2007). “A Design Science Research Methodology for Information Systems Research”. *Journal of Management Information Systems* 24.3, pp. 45–77. ISSN: 0742-1222. DOI: 10.2753/MIS0742-1222240302.

Powell, Thomas C. (1992). “Strategic planning as competitive advantage”. *Strategic Management Journal* 13.7, pp. 551–558. ISSN: 01432095. DOI: 10.1002/smj.4250130707.

Enabling Privacy and Collaboration: The Role of Privacy Enhancing Technologies in the Future of Artificial Intelligence

Authors

Sebastian Duda, Marc Principato, Tobias Guggenberger, Nils Urbach

Abstract

Artificial Intelligence (AI) is revolutionizing industries by enabling advanced decision-making and predictive insights (Agrawal et al., 2018). Yet, its full potential is often constrained when crucial training data remains inaccessible due to confidentiality and privacy concerns. Privacy Enhancing Technologies (PETs) offer promising avenues to overcome these limitations by allowing data utilization without exposing raw information.

However, research on PETs in AI has largely centered on technical implementations, leaving the information systems (IS) perspective underexplored. Drawing on Aral et al. (2013), this paper synthesizes current literature by conducting a systematic literature review based on Kitchenham and Charters (2007) and Webster and Watson (2002). Furthermore, we identify three key topics for future research: (1) Integrating PETs into AI development necessitates balancing data security, computational overhead, and model performance – what we conceptualize as the PETs4AI-Trilemma. (2) Privacy is better understood as a continuum rather than a binary property, yet suitable metrics for measuring privacy levels remain elusive. (3) Economic evaluations of PET adoption must consider a complex interplay of costs, benefits, and contextual factors, the intricacies of which are not fully understood.

Our findings suggest that while PETs can unlock novel data sources and use cases, their performance trade-offs and economic uncertainties demand careful evaluation. We conclude the paper by proposing a research agenda to address the PETs in AI development from an IS perspective.

Keywords

Artificial Intelligence, Privacy-Enhancing Technologies, Distributed Collaborative Machine Learning, Information Systems Management, Technology Convergence, Research Agenda

References

Agrawal, Ajay, Joshua Gans, and Avi Goldfarb (2018). *Prediction machines*. Boston, MA: Harvard Business Review Press.

Aral, Sinan, Chrysanthos Dellarocas, and David Godes (2013). “Introduction to the Special Issue – Social Media and Business Transformation: A Framework for Research”. *Information Systems Research* 24.1, pp. 3–13. ISSN: 1047-7047. DOI: 10.1287/isre.1120.0470.

Kitchenham, Barbara and Stuart Charters (2007). “Guidelines for performing Systematic Literature Reviews in Software Engineering”. 2.

Webster, Jane and Richard T. Watson (2002). “Analyzing the Past to Prepare for the Future: Writing a Literature Review”. *MIS Quarterly* 26.2, pp. xiii–xxiii. ISSN: 02767783.

Toward Data-Sovereign Prescriptive Process Monitoring: A Federated Learning Approach

Authors

Linda Moder, Sebastian Duda, Lukas Willburger, Roberto Kraus Caballero, Björn Häckel, Maximilian Röglinger, Nils Urbach

Abstract

In today's dynamic business environment, organizations continuously seek to refine their processes to stay competitive. This requires both immediate adaptations and long-term design alterations for process improvement. Process mining plays a crucial role by enabling data-driven optimization, particularly through prescriptive process monitoring. This approach allows real-time process enhancement by suggesting suitable interventions, helping organizations make informed decisions quickly (Kubrak et al., 2022).

Most current methods focus on determining which interventions to apply and when rather than deriving interventions from execution data like event logs. While some techniques apply machine learning to extract actions from event logs, they often target single organizations. However, many processes span similar functions across different organizations, evident in domains like healthcare or common processes such as order-to-cash (Khan et al., 2021; Rafiei and van der Aalst, 2023). This presents opportunities to learn from interorganizational practices, though challenges in data privacy and confidentiality arise (Elkoumy et al., 2022; Rafiei and van der Aalst, 2023).

The paper at hand investigates designing a data-sovereign approach for interorganizational prescriptive process monitoring, proposing federated learning as a foundation. Federated learning, known for its promise in privacy-preserving machine learning, shows poten-

tial for process mining applications like process discovery (Khan et al., 2021). Following design science research methodology, the study develops and evaluates a federated learning-based approach consisting of a training phase for aggregating model parameters and a run phase for providing localized recommendations. The produced software prototype demonstrates the approach's practicality, achieving data-sovereign interorganizational prescriptive process monitoring.

This research marks a step toward sophisticated, secure data collaboration across organizations, facilitating the exchange of best practices without compromising privacy. It contributes to the convergence of prescriptive process monitoring, data sovereignty, and federated learning, providing a foundation for future innovations in the field.

Keywords

Prescriptive process monitoring; interorganizational process optimization; federated process mining; federated learning; data sovereignty

References

Elkoumy, Gamal, Stephan A. Fahrenkrog-Petersen, Mohammadreza Fani Sani, Agnes Koschmider, Felix Mannhardt, Saskia Nu~ nez von Voigt, Majid Rafiei, and Leopold von Waldthausen (2022). "Privacy and Confidentiality in Process Mining: Threats and Research Challenges". *ACM Transactions on Management Information Systems* 13.1, pp. 1–17. ISSN: 2158-656X. DOI: 10.1145/3468877.

Khan, Asjad, Aditya Ghose, and Hoa Dam (2021). "Cross-Silo Process Mining with Federated Learning". In: *Service-Oriented Computing*. Ed. by Hakim Hacid, Odej Kao, Massimo Mecella, Naouel Moha, and Hye-young Paik. Vol. 13121. Lecture Notes in Computer Science. Cham: Springer International Publishing, pp. 612–626. ISBN: 978-3-030-91430-1. DOI: 10.1007/978-3-030-91431-8_38.

Kubrak, Kateryna, Fredrik Milani, Alexander Nolte, and Marlon Dumas (2022). "Prescriptive process monitoring: Quo vadis?" *PeerJ. Computer science* 8, e1097. DOI: 10.7717/peerj-cs.1097.

Rafiei, Majid and Wil van der Aalst (2023). "An Abstraction-Based Approach for Privacy-Aware Federated Process Mining". *IEEE Access* 11, pp. 33697–33714. DOI: 10.1109/ACCESS.2023.3263673.

Designing Effective Collaborative Learning Systems: Demand Forecasting in Supply Chains Using Distributed Data

Authors

Sebastian Duda, Tobias Guggenberger, Domenique Zipperling, Niklas Kühl

Abstract

The bullwhip effect presents a significant challenge in supply chain management (Forrester, 1961), and accurate demand forecasting has been recognized as a critical strategy to mitigate it (Chen et al., 2000). The literature has emphasized various approaches to enhance forecasting accuracy – from statistical approaches like the moving average (Chen et al., 2000) or exponential smoothing (Bayraktar et al., 2008) to machine learning (ML) approaches (Carbonneau et al., 2008). While ML has great potential in demand forecasting (Carbonneau et al., 2008), data scarcity limits the usage of machine learning models, and the potential of levering distributive collaborative machine learning has been largely overlooked.

To address this, we introduce an innovative artifact designed to utilize distributed data from multiple companies in a single supply chain level to collaboratively train machine learning models. By combining scarce data from multiple sources, we aim to enhance forecasting accuracy, thus enhancing supply chain efficiency. We implement the echelon design science research (DSR) approach from Tuunanen et al. (2024) based on Peffers et al.'s (2007) DSR approach to design our approach. We combine design knowledge from different sources – (1) Vepakomma et al.'s (2018) split learning framework, (2)

Poirot et al.'s (2019) u-shaped configuration, and (3) Jin et al.'s (2023) multitask learning architecture – to meet our objectives.

We evaluated our approach using synthetic (Bayraktar et al., 2008) and real-world data (Statistics Canada, 2024) and concluded that our approach has the potential to improve demand forecasting in complex market scenarios.

Keywords

Supply chains, bullwhip effect, horizontal information sharing, collaborative demand forecasting, distributed collaborative machine learning

References

Bayraktar, Erkan, S. C. Lenny Koh, A. Gunasekaran, Kazim Sari, and Ekrem Tatoglu (2008). "The role of forecasting on bullwhip effect for E-SCM applications". *International Journal of Production Economics* 113.1, pp. 193–204. ISSN: 09255273. DOI: 10.1016/j.ijpe.2007.03.024.

Carbonneau, Real, Kevin Laframboise, and Rustam Vahidov (2008). "Application of machine learning techniques for supply chain demand forecasting". *European Journal of Operational Research* 184.3, pp. 1140–1154. ISSN: 03772217. DOI: 10.1016/j.ejor.2006.12.004.

Chen, Frank, Jennifer K. Ryan, and David Simchi-Levi (2000). "The impact of exponential smoothing forecasts on the bullwhip effect". *Naval Research Logistics (NRL)* 47.4, pp. 269–286. ISSN: 1520-6750. DOI: 10.1002/(SICI)1520-6750(200006)47:4{\textless}269::AID-NAV1{\textgreater}3.0.CO;2-Q.

Forrester, Jay Wright (1961). *Industrial dynamics*. Portland, Oregon and Cambridge, Massachusetts: Productivity Press and M.I.T. Press Massachusetts Institute of Technology. ISBN: 0915299887.

Jin, David, Niclas Kannengießer, Sascha Rank, and Ali Sunyaev (2023). *A Design Toolbox for the Development of Collaborative Distributed Machine Learning Systems*.

Peffers, Ken, Tuure Tuunanen, Marcus A. Rothenberger, and Samir Chatterjee (2007). "A Design Science Research Methodology for Information Systems Research". *Journal of Management Information Systems* 24.3, pp. 45–77. ISSN: 0742-1222. DOI: 10.2753/MIS0742-1222240302.

Poirot, Maarten G., Praneeth Vepakomma, Ken Chang, Jayashree Kalpathy-Cramer, Rajiv Gupta, and Ramesh Raskar (2019). *Split Learning for collaborative deep learning in healthcare*. arXiv: 1912.12115.

Statistics Canada (2024). *Manufacturers' sales, inventories, orders and inventory to sales ratios in dairy product manufacturing*. DOI: 10.25318/1610004701-eng.

Tuunanen, Tuure, Robert Winter, and Jan vom Brocke (2024). "Dealing with Complexity in Design Science Research: A Methodology Using Design Echelons". *MIS Quarterly* 48.2, pp. 427–458. ISSN: 02767783. DOI: 10.25300/MISQ/2023/16700.

Vepakomma, Praneeth, Otkrist Gupta, Tristan Swedish, and Ramesh Raskar (2018). *Split learning for health: Distributed deep learning without sharing raw patient data*. DOI: 10.48550/arXiv.1812.00564.

Understanding the Machine Economy: Combining Findings From Science and Practice

Authors

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Abstract

The paper addresses the need to understand the Machine Economy (ME) by integrating insights from both scientific and practical perspectives. The motivation stems from the interdisciplinary nature of the ME domain, which presents a challenge in consolidating differing viewpoints. The research gap is the lack of a comprehensive model that adequately represents the ME, merging theoretical propositions with real-world practices. The central research question seeks to establish a five-layer model that encapsulates the key elements of the ME.

The theoretical underpinning of the study derives from a structured literature review, following guidelines by Webster and Watson (2002). The final set of eleven articles informed the development of the ex-ante propositions foundational to the paper's analysis and model construction.

Employing a qualitative research paradigm, the study first involved a rigorous literature review followed by semi-structured interviews with domain experts. The interviews were adapted during the conversations to capture emergent themes. The research process aligned with established qualitative methods, as outlined by Corbin and Strauss (1990). The iterative workshop sessions with authors led to the refinement of ex-post propositions related to the ME. The research culminated in the development of a five-layer model for the ME. This model integrates insights from both theoretical exploration and practical

validation, resulting in a comprehensive framework that reflects the various dimensions and interactions within the ME.

The discussion highlights the importance of merging theoretical insights with practical applications to fully capture the complexity of the ME. One limitation acknowledged is the reliance on a limited set of sources, which might not encapsulate the entire spectrum of research in the ME field. Future research directions include expanding the scope of the literature review and incorporating a more diverse set of expert perspectives.

Keywords

Machine Economy, Machine-to-Machine (M2M) Communication, Economy of Things, Propositions, Layer Model

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References

Corbin, Juliet M. and Anselm Strauss (1990). "Grounded theory research: Procedures, canons, and evaluative criteria". *Qualitative Sociology* 13.1, pp. 3–21. ISSN: 1573-7837. DOI: 10.1007/BF00988593.

Webster, Jane and Richard T. Watson (2002). "Analyzing the Past to Prepare for the Future: Writing a Literature Review". *MIS Quarterly* 26.2, pp. xiii–xxiii. ISSN: 02767783.

Forecasting the Emerging Machine Economy: Toward a Maturity Model

Authors

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Abstract

Recent advances in emerging digital technologies ultimately enable economically autonomous acting machines (Ågerfalk, 2020). Such machines are leading to an emerging machine economy, which practitioners and academics alike expect to have profound market potential. However, to date, the interaction of autonomous machines is limited by a common understanding of how such a machine economy manifests in the future.

To address this issue, we followed the established maturity model development method of Becker et al. (2009) to develop the Machine Economy Entities Maturity Model (MEEMM). We started to build the maturity model based on the existing literature, which we captured using Webster and Watson's (2002) literature review methodology. Further, we extended and evaluated our knowledge using 22 expert interviews.

Our proposed maturity model has six dimensions and eleven sub-dimensions outlining the machine's capabilities required to participate in the machine economy. We thereby bridge the gap in literature between conceptual work and research focusing on technical aspects of the machine economy vision.

Our MEEMM provides a common understanding of the emerging machine economy and identifies development paths towards it. Companies might use the MEEMM to make their organization's product portfolio ready for the machine economy and derive future visions for their products. We thereby provide a starting point for a more detailed discussion

about the potential and corresponding challenges of a future machine economy in both academia and practice.

Keywords

Machine Economy, Maturity Model, Autonomous Agents, Machine Customers

References

Ågerfalk, Pär J (2020). "Artificial intelligence as digital agency". *European Journal of Information Systems* 29.1, pp. 1–8.

Becker, Jörg, Ralf Knackstedt, and Jens Pöppelbuß (2009). "Developing Maturity Models for IT Management". *Business & Information Systems Engineering* 1.3, pp. 213–222. ISSN: 1867-0202. DOI: 10.1007/s12599-009-0044-5.

Webster, Jane and Richard T. Watson (2002). "Analyzing the Past to Prepare for the Future: Writing a Literature Review". *MIS Quarterly* 26.2, pp. xiii–xxiii. ISSN: 02767783.