UNIVERSITÄT BAYREUTH

Understanding the Interworking of Humans and AI to Design Purposeful Smart Services

Dissertation

zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

der Rechts- und Wirtschaftswissenschaftlichen Fakultät

der Universität Bayreuth

Vorgelegt

von

Lukas Andreas Fabri

aus

München

Dekan:	Prof. Dr. André Meyer
Erstberichterstatter:	Prof. Dr. Björn Häckel
Zweitberichterstatter:	Prof. Dr. Maximilian Röglinger
Datum der mündlichen Prüfung:	05.12.2023

Copyright Statement

Abstract

Artificial intelligence (AI) heralds a new age of information technology, offering promising opportunities. These opportunities contribute to the well-being of individuals, the success and innovation of businesses, and the prosperity and progress of society. In particular, the benefits of AI for businesses lie in its ability to perform complex tasks previously considered to be the domain of humans. This growing potential of business applications has led to significant investments, which has led to copious amounts of AI use cases. The conventional approach of AI use cases has been to treat humans and machines as substitutes that can replace one another in the execution of tasks. However, combining the complementary strengths of AI-enabled systems and human agents can offer distinct benefits, e.g., performance improvements. Consequently, this combination paves the way for a new generation of highly performant services that create new areas of value creation.

In this vein, this doctoral thesis takes a twofold approach: First, an integrative perspective on *understanding human-AI hybrids as the foundation for smart services* is required to understand better the nature of human-AI-hybrids and analyze their range of roles in depth. Hence, Research Article #1 presents a taxonomy that provides a clear structure for the collaborative interworking of human agents and AI-enabled systems. Second, exploring the opportunities and challenges of AI-driven services in the manufacturing and energy sectors is imperative to develop *artifacts to structure and derive actionable recommendations for designing purposeful smart services*. Research Article #2 provides a decision model for the manufacturing industry to support industrial companies that act as full-service providers in selecting economically advantageous predictive maintenance algorithms. Research Article #3 develops a taxonomy to structure smart energy service characteristics into four entities and 15 dimensions to deepen the understanding of smart services in the energy sector. Taking on a business model perspective, Research Article #4 enables structuring and developing business models for smart energy services like non-intrusive load monitoring in the industrial sector. To support the more widespread use of non-intrusive load monitoring for industrial applications and reduce data challenges, Research Article #5 develops an active learning model using real-world data.

This doctoral thesis contributes to understanding human-AI hybrids as a foundation for purposeful smart services. It proposes artifacts for structuring smart services and deriving actionable recommendations fostering more expansive use of smart services in the future.

Table of Contents

I Introduction

1 Motivation

Artificial intelligence (AI) currently heralds a new age of information technology, offering promising opportunities (Ågerfalk 2020; Berente et al. 2021). These opportunities are believed to contribute to the well-being of individuals, the success and innovation of businesses, and the prosperity and progress of society (Thiebes et al. 2021). Studies by McKinsey, PricewaterhouseCoopers, and TeamLease estimate that the utilization of AI could yield an additional worldwide economic output of 13 to 16 trillion USD by 2030 (Bughin et al. 2018; Rao and Verweij 2017; TeamLease Digital 2023). The benefits of AI for businesses lie in its ability to perform complex tasks previously thought to be the domain of humans (Lins et al. 2021). Examples of such complex tasks include analyzing medical data to enable innovative diagnostics by assisting physicians (Al-Antari 2023) or analyzing vast amounts of market data in real-time to enable faster stock portfolio management (Flavián et al. 2022). At the same time, this growing potential of business applications has led to significant investments and, as a result, a plethora of AI applications (Dellermann et al. 2019a).

A part of those AI applications are smart services. Smart services are data-driven applications or systems that use advanced technologies (e.g., AI) to provide users with personalized, contextual, and proactive service (Beverungen et al. 2019; Knote et al. 2021; Wuenderlich et al. 2015). Examples of smart services are telematics tariffs in car insurance (i.e., calculating individual tariffs based on transmitted driving data) or smart home solutions (e.g., automated indoor climate improvement by sensor measurement and automatic (roof) window opening). Smart services offer companies numerous new opportunities to expand their existing service portfolios and create new business opportunities (Beverungen et al. 2019; Knote et al. 2021). Consequently, there have been many advances in the research area of designing smart services, predominantly with a technological focus. However, the perspective on the interaction between humans and machines in smart services is still underrepresented in research. Nevertheless, a deep understanding of this interplay is necessary to make sensible design decisions for smart services since smart services usually involve a human and an IT component that must be closely intertwined. Therefore, a multidimensional socio-techno-economic perspective is necessary for purposeful design decisions. In this vein, in addition to the current, predominantly technological focus, it is essential to cover both an organizational and an economic perspective. Designing in this context refers to the conception and building of a smart service using knowledge derived from theory and related artifacts to support the practical application of smart services (Hevner 2007; Maglio and Spohrer 2013). In this vein, research lacks guidelines for designing and implementing purposeful smart services in practice (Anke et al. 2020; Larson 2016; Wolf et al. 2020). This lack of guidance leads to various economic problems (e.g., missing commercially viable business models and monetization) and organizational challenges (e.g., impact on distribution structure, cultural and competency issues). Against this backdrop, research should adress not only technological challenges but also focus on organizational and economical challenges related to smart services. This is of particular interest to the IS research community as it adresses challenges at the interface between IT and organizations (Peffers et al. 2020).

Within the application of smart services and, thus, at the intersection of IT and organizations, human factors are especially pivotal (Larson 2016). Skills previously dominated by humans can be replaced by AI, changing the way people work. For example, an AI can perform automated data analysis much faster than a human, leaving the human more time for customer contact. This change creates a variety of new service opportunities but also brings challenges such as very heterogeneous ways for humans and AI to work together. It is, therefore, essential to have a clear picture of how humans and AI will work together as a basis for designing targeted, smart services (Loureiro et al. 2021; Østerlund et al. 2021). Hitherto, the conventional approach to AI applications has been to treat humans and machines as substitutes that can replace one another in the performance of tasks (Daugherty and Wilson 2018; Raisch and Krakowski 2021). However, certain aspects of tasks are likely to align well with the capabilities of AI-enabled systems, while others are likely to correspond better with those of human agents (Daugherty and Wilson 2018; Rai et al. 2019). Human agents and AI-enabled systems perform different roles and interactions to facilitate collaborative work (Daugherty and Wilson 2018; Davenport 2018). In line with this, recent studies have revealed that this limited perspective (i.e., human and AI as substitutes) has had two unfortunate consequences: First, a disproportionately large focus on automation and second, a tendency to neglect the powerful interworking and resulting benefits that occur when humans and AI augment each other (Dellermann et al. 2019b; Rai et al. 2019; Seeber et al. 2020). Recent literature emphasizes that combining the complementary strengths of AI-enabled systems and human agents can offer distinct benefits, including increased organizational knowledge and performance improvements (Fügener et al. 2021; Maedche et al. 2019; Sturm et al. 2021). Consequently, the integrated perspective on human-AI hybrids addresses the issues above and paves the way for a new generation of highly performant smart services that create new areas of value creation (Agrawal et al. 2018; Sjödin et al. 2021).

Despite the promising opportunities to improve value creation and profitability, several economical and organizational challenges exist in designing and implementing smart services (Heuchert et al. 2020; Klein et al. 2018; Pressmair et al. 2021; Töytäri et al. 2017). To realize these opportunities, research must address three key challenges in particular (e.g., Klein et al. (2018), Maglio and Lim (2016), Marquardt (2017), Paukstadt et al. (2019b)): 1) missing specifications for the structure and design of sector-specific or application-specific smart services, 2) insufficient integration of the economic perspective for designing smart services, and 3) inadequate data availability and quality.

First, a well-structured but purely overarching perspective (e.g., Paukstadt et al. (2019b)) is insufficient for many sectors or applications because it lacks specific characteristics for designing purposeful smart services. An in-depth consideration of smart services' specific characteristics (e.g., specific customers, data types, value propositions) is necessary for an organized knowledge structure to support an informed decision (e.g., how to concept and build a smart service in the energy context). For this case, it is crucial to know and structure the context of specific smart services (e.g., specifics of smart services in the energy context, like energy-specific input data or use cases like light or heating). Therefore, a detailed specification of smart services is also necessary at the sector or application level. For example, in the smart city domain, Pourzolfaghar and Helfert (2017) have provided such a specification of smart services (e.g., different aspects of purposes like sustainability and social aspects), thus contributing to the design of more effective smart services to respond to citizens' concerns and meet smart city quality requirements.

Second, the economic perspective of smart services is often not sufficiently considered, e.g., how smart services can be economically marketed and operated to complement the company's traditional product offerings (Klein et al. 2018; Winter 2023). In addition, the emerging complexity of value creation and the shift from product- to service-oriented businesses (especially in manufacturing) require companies to consider new business models and customer-centric monetization. Consequently, companies need guidance in developing economically viable business models (Bundesministerium für Wirtschaft und Energie (BMWi) 2019; Geissdoerfer et al. 2018; Spieth et al. 2014). Therefore, an economic perspective is necessary to exploit the promising value-creation potential of smart services and operate them not only functionally, but also economically. Therefore, better guidance on the economic design of smart services is needed.

Third, smart services are data-based and directly depend on data availability and quality. However, businesses often face challenges in meeting the necessary data requirements regarding quality, quantity, and other barriers (Klein et al. 2018; Preidel and Stark 2021). These barriers include, for example, the complexity of networking across multiple stakeholders within an ecosystem (e.g., clarifying data sharing and ownership). There is also the challenge of merging data from different sources (both internal and external): In the example of a smart service in the energy sector, data on the company's electricity consumption, the electricity generated by its power plants, market price forecasts, and weather data can be incorporated, among others. In addition, the data may be partly structured and partly unstructured. Furthermore, industrial companies often face the problem of costly retrofitting of existing equipment with sensors to create a foundation for smart services.

To address these challenges and reduce barriers for designing of smart services, this doctoral thesis will address selected issues related to the above challenges in two selected sectors. These two sectors are industrial manufacturing and energy services.

First, companies face changes in industrial manufacturing due to globalization, cost pressures, and supply chain bottlenecks. Increased competition forces companies to consider innovative and technology-driven changes, economic factors, and product differentiators (e.g., sustainable products and excellent customer service) to remain competitive. Hybrid value creation and smart services are particularly relevant in shifting from product-oriented to service-oriented businesses. For example, smart services can help leverage existing field data and knowledge about customers to create new customer value, enabling high margins on smart services and high scalability. Incumbents need to develop new digital value propositions, i.e., smart services, to meet the ever-increasing competitive pressure. Since maintenance is one of the most significant cost drivers in industrial manufacturing, predictive maintenance (PdM) is an auspicious smart service (Windmark et al. 2018). Combining technology and economics, PdM leverages the interworking of human expertise on machines and failure types with the analytical capabilities of AI to predict upcoming failures and corresponding maintenance needs to avoid downtime and reduce maintenance costs (Chen et al. 2019; World Economic Forum 2015). Therefore, PdM pursues and supports three core objectives: First, increased provider efficiency in maintenance operations and scheduling to save costs. Second, this enhanced equipment availability increases customer satisfaction and creates greater efficiency for the customer by reducing production bottlenecks or lost revenue due to machine downtimes. Third, this combination of technology and economics provides the basis for new business models, such as pay-per-use. In summary, the economic perspective is essential for the sensible design of PdM-based business models, and maintenance strategies. The technological perspective is well researched from a design perspective, so there is a plethora of algorithms, selection criteria, and decision support tools, as the research focus is mainly on the performance metrics of statistical algorithms (e.g., event prediction accuracy). Hitherto, the economic perspective has been underrepresented, especially in the industrial domain.

Second, the energy services sector is developing rapidly and is one of the sectors of the economy that can benefit most from smart services (Kratochwill et al. 2020). Given the need to address climate change in all sectors, not just industry, focusing on energy efficiency and CO2 savings is critical. Due to the complexity of environmental changes and energy systems, AI is expected to support humans in diverse use cases, such as minimizing environmental load or optimizing energy storage and distribution (Ahmad et al. 2022; Liu et al. 2022). Therefore, AI is gaining importance due to its offering opportunities (European Commission 2020). For example, AI can help intelligently manage volatile supply by predicting renewable energy generation and demand (Moreno et al. 2019). Further, AI can also support consumers, such as in smart homes, by analyzing behavior patterns and adjusting energy consumption accordingly (Lee et al. 2023). However, this requires a high level of coordination and information exchange between stakeholders, including energy suppliers, grid operators, and consumers. Providing smart services in the energy sector can facilitate this coordination and enable real-time communication (Paukstadt and Becker 2021a, 2021b). For example, non-intrusive load monitoring (NILM) allows identifying individual consumers in an aggregated power consumption load profile measured from a single meter using algorithms and machine learning (Ruano et al. 2019). Using a single measurement device, NILM reduces the need for coordination and enables improved streamlined information sharing. Despite these promising opportunities and demand for such smart services, 80% of energy startups funded in 2010 at the height of the "cleantech boom" failed to meet their investors' expectations ten years later (Bennett et al. 2021). One possible reason could be the lack of alignment with human needs when using AI in the energy sector (e.g., trust and acceptance of the service offering). Due to their novelty and heterogeneity, little research supports designing smart services in the energy sector (Paukstadt and Becker 2021a). In addition, challenges are associated with implementing these smart services, such as the lack of a business model perspective and the difficulty of collecting appropriate data. An integrated design perspective is needed to address these barriers, considering both technical and economic aspects.

Although the powerful combination of AI and humans is expected to deliver new, value-generating smart services, many organizations face challenges in realizing the value of using AI (Ransbotham et al. 2020). This doctoral thesis aims to reduce the barriers to *designing purposeful smart services* by a twofold approach: On the one hand, an integrative perspective on *understanding human-AI hybrids as the foundation for smart services* is taken to understand better the nature of human-AI hybrids and analyze their range of roles in depth. On the other hand, this doctoral thesis aims to contribute to the challenges above by developing *artifacts to structure smart services and derive actionable recommendations* for designing purposeful smart services.

2 Research Aim & Structure

This doctoral thesis addresses the outlined challenges of *designing purposeful smart services* in the previous section in a twofold approach. It builds on existing research, such as taxonomies, business model archetypes, and studies, to develop applicable artifacts that deliver descriptive knowledge and offer actionable recommendations for designing purposeful smart services.

First, regarding *understanding human-AI hybrids as the foundation for smart services*, previous research is undoubtedly detailed but often focuses on either a technical or a social perspective. However, an integrative perspective is needed to focus on the complementary interaction of human agents and AI-enabled systems to address the multiple interdependencies between humans and AI (Jarrahi 2018). There is agreement among several scientists on this point (Agrawal et al. 2018; Daugherty and Wilson 2018; Traumer et al. 2017), with Davenport and Ronanki (2018) inferring from their survey of 250 executives that companies are more successful in developing AI use cases when they focus on augmenting human capabilities rather than replacing them. Furthermore, research has yet to embrace a holistic perspective that acknowledges the contribution of human agents and AI-enabled systems as separate entities with distinct, globally intra-act characteristics of human-AI hybrids (Rai et al. 2019). Hence, this doctoral thesis aims to contribute to this challenge by drawing from weak sociomateriality as justificatory knowledge to the descriptive knowledge on human-AI hybrids and the ongoing discourse on human-AI collaboration (Benbya et al. 2021; Dwivedi et al. 2021; Raisch and Krakowski 2021; Seeber et al. 2020) by providing 1) a well-founded taxonomy of human-AI hybrids and 2) archetypes of human-AI hybrids. The taxonomy provides a holistic structure to human-AI hybrids and connects the discourse on human-AI collaborations (Dellermann et al. 2019b; Maedche et al. 2019; Rai et al. 2019). The taxonomy provides a new, balanced perspective that considers the characteristics and capabilities of both human agents and AI-enabled systems. In this way, the taxonomy makes it easy to classify how humans and AI work together, enabling decision makers to analyze and understand human-AI hybrids and how to use them wisely. In addition, the archetypes of human-AI hybrids, with their distinctive combinations of characteristics, facilitate a deeper understanding of how human-AI hybrids work in concrete, practical terms.

Second, this doctoral thesis offers several insights regarding *artifacts to structure smart services and derive actionable recommendations for designing purposeful smart services*. In this vein, this doctoral thesis addresses selected challenges in the industrial manufacturing and energy service sectors: 1) missing specifications for the structure and design of sector-specific or application-specific smart services, 2) insufficient integration of the economic perspective for designing smart services, and 3) inadequate data availability and quality.

In the industrial manufacturing sector, this doctoral thesis aims to address the challenge of insufficient integration of the economic perspective. Especially with cost pressure, global competition, and the shift from product-oriented to service-oriented business, focusing on PdM in industrial manufacturing is a promising approach for a valuable smart service. However, the current research on the operation of PdM is mainly driven from a technical perspective. As a result, not the entire value potential may be realized if an algorithm is selected purely from a statistical perspective based on performance metrics without integrating an economic perspective. Therefore, this doctoral thesis covers an economic design perspective for PdM in industrial manufacturing by developing a decision model to support decision-makers in designing economically viable smart services. The decision model focuses on economic criteria in selecting algorithms to predict upcoming failures and maintenance needs.

This doctoral thesis contributes to all three challenges above in the energy service sector. First, due to their novelty and heterogeneity, research on the design of smart services in the energy sector is scarce (Paukstadt and Becker 2021a). As a result, while partial research findings are available (e.g., on the general structure of smart services or individual use cases), there is a lack of an integrative perspective that enables a common, descriptive understanding of the complex and heterogeneous nature of smart services in the energy sector. Therefore, this doctoral thesis presents a taxonomy that supports researchers and practitioners in describing and analyzing SES and connects smart service research and energy service research. Second, regarding the economic perspective support for designing and developing a successful business model is missing for a wider use of smart services in the energy sector. Therefore, a business model framework is developed to contribute a practical and strategic framework for concretizing and implementing business ideas on SES. Third, challenges regarding adequate data quantity and quality exist. As a result, applications are challenging to implement. For example, NILM is already used extensively in private households, but transferability to industrial companies is problematic due to a lack of data quantity and quality. Therefore, this dissertation contributes to increasing data quality through active learning.

To summarize, the overarching objective of this work is to examine AI´s impact on *designing purposeful smart services* from a twofold perspective: First, the doctoral thesis takes an overarching perspective on the powerful combination of *human-AI hybrids*, which has a profound impact on smart services. Second, the doctoral thesis takes a detailed perspective on several *artifacts to structure smart services and derive actionable recommendations for designing purposeful smart services.*

As a cumulative doctoral thesis, this work consists of five research articles that address its fundamental topic using different qualitative and quantitative methodological approaches, different forms of empirical evidence, and different perspectives to design purposeful smart services (s. Figure 1). Therefore, this doctoral thesis offers a new theoretical perspective on human-AI hybrids and conceptualizing the interaction between humans and AI-enabled systems. This provides an understanding of human-AI hybrids as the foundation for designing purposeful smart services. In addition, the research contributions provide artifacts that structure smart services and derive actionable recommendations. Consequently, all the research contributions in this doctoral thesis relate to designing purposeful smart services.

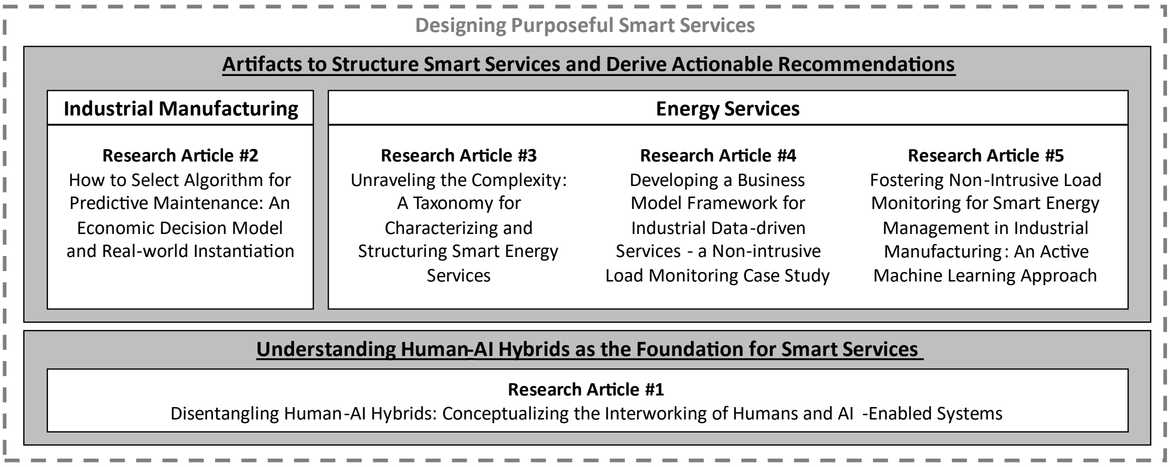

Figure 1: Assignment of the research articles to the topics structuring this doctoral thesis

Section II.1 presents Research Article #1, which addresses an *understanding of human-AI hybrids as the foundation for smart services*. The taxonomy of human-AI hybrids puts a clear, descriptive structure to the collaborative interworking of human agents and AI-enabled systems and allows its analyzing (Nickerson et al. 2013; Oberländer et al. 2019).

In doing so, the taxonomy provides a new, balanced perspective that considers human agents' and AI-enabled systems' characteristics and capabilities. The taxonomy facilitates classifying human-AI interactions along three entities (i.e., human, AI, and socio-material practices). In doing so, it enables decision-makers to analyze and understand human-AI hybrids and their wise use. Moreover, it lets decision-makers comprehend the characteristics that constitute specific human-AI hybrids and what these characteristics might entail. Further, the work derives five archetypes of human-AI hybrids, each illustrating different AI-enabled systems' roles in those collaborative interworking scenarios. Building on an extensive knowledge base, these archetypes offer insights into the prototypical implementation of human-AI hybrids in the real world. In doing so, the taxonomy embeds itself in previous research and serves as a catalytic means for the progress of broader theorizing on human-AI hybrids and the future of work in general. Furthermore, it sheds light on how human agents and AI-enabled systems could combine their strengths and achieve results that would be impossible if they acted separately.

Section II.2 presents Research Articles #2, #3, #4, and #5, which develop *artifacts to structure smart services and derive actionable recommendations.* Research Article #2 provides an artifact in the form of a decision model intending to support industrial companies in selecting economically advantageous PdM algorithms. Hence, the decision model provides economic insights into the trade-off between the two general types of prediction errors (i.e., false positive – false alarm and false negative - ignored failure). This integration enables the decision model to give the user an economic perspective when designing smart services. Research Articles #3, #4, and #5 focus on energy research topics, especially smart energy services (SES). Research Article #3 provides a deeper understanding of SES's essential characteristics by reviewing the scientific literature and developing a taxonomy to structure SES's characteristics into four entities and 15 dimensions. The taxonomy supports researchers and practitioners in describing and analyzing the essential characteristics of SES and offers a theoretically and empirically validated foundation for understanding SES. Following a design science research approach, Research Article #4 presents a business model framework that enables structuring and developing business models for NILM as a representative SES for industrial applications. Research Article #4 contributes to literature and practice by complementing the ongoing, mainly technological-focused research activities by providing a methodically sound and practical business model framework. To foster wider use of NILM for industrial applications and reduce data challenges, Research Article #5 develops an active learning model using real-world data and comparing three disaggregation algorithms with a benchmark model by efficiently selecting a subset of training data.

Section III concludes this doctoral thesis with a summary of key findings, limitations, and directions for future research. Section IV lists the references used in this doctoral thesis. Finally, the Appendix in section V provides an index of the research articles presented in this doctoral thesis (V.1), my contributions (V.2), and the overview of included research articles (V.3 to V.7)

II Building Purposeful Smart Services

1 Understanding Human-AI Hybrids as the Foundation for Smart Services

AI, especially its application, affects organizations by offering promising potential for enhancing and augmenting human capabilities. With increasingly sophisticated AI-related technologies, researchers and practitioners identify numerous application scenarios in organizations (Bughin et al. 2018). Although the necessity for human-AI collaboration has already been confirmed, insights on the fruitful combination of human agents and AI-enabled systems are sparse. Moreover, little effort has been made to holistically analyze and understand the entangled interworking in the so-called human-AI hybrids, which form when human agents and AI-enabled systems collaborate. Simultaneously, the rise of potential business applications has led to significant investments from organizations resulting in copious amounts of AI pilot projects or proof of concepts (Dellermann et al. 2019a; Pumplun et al. 2019). As outlined in the Introduction, the traditional approach in those initiatives has been to view humans and machines as substitutes that can replace each other in performing tasks and jobs (Daugherty and Wilson 2018; Raisch and Krakowski 2021). However, recent studies revealed that this binary perspective on AI technologies not only results in an over-emphasized focus on automation but also in a neglection of the powerful collaboration that occurs when humans and machines augment each other (Dellermann et al. 2019b; Rai et al. 2019; Seeber et al. 2020). In the current literature, many studies focus on either the technical or the social perspective, offering detailed but fragmented information and insights. Because of the highly entangled nature of the interworking of human agents and AI-enabled systems, emphasizing an integrative perspective that focuses on the complementary cooperation of both is paramount (Jarrahi 2018). This notion is backed by many experts in the field (e.g., Agrawal et al. (2018), Daugherty and Wilson (2018), Davenport (2018), Traumer et al. (2017)), with Davenport and Ronanki (2018) inferring from their survey of 250 executives that companies are more successful in developing AI use cases when they focus on augmenting human capabilities rather than replacing them. However, the knowledge of the collaborative interworking of human agents and AI-enabled systems from a holistic perspective is sparse (Davenport 2018), which leaves us with an incomplete picture and a missing ground for further discussion and sensemaking (Sarker et al. 2019). So far, a differentiated view of the precise ways in which human agents and AI-enabled systems can complement one another when performing tasks is missing (Rai et al. 2019). Therefore, Rai et al. (2019) call for studies on the tasks and roles of humans and AI in so-called human-AI hybrids, a term they use to describe the new collaborative forms of interworking between human agents and AI-enabled systems. Against this backdrop, Research Article #1 proposes a taxonomy of human-AI hybrids adopting Nickerson et al.’s (2013) iterative taxonomy development method that allows to understand and analyze the complex domain of the interworking of human agents and AI-enabled systems (Nickerson et al. 2013; Oberländer et al. 2019). To allow for a deeper understanding of the implications of the symbiotic interworking in human-AI hybrids, a hybrid lens that combines sociomateriality and a pre-structured differentiation of the theory of sociotechnical systems is applied (Kautz and Jensen 2013; Gaskin et al. 2014). Research Article #1 uses this lens to present a taxonomy of nine dimensions and 38 characteristics.

Figure 2 presents the final taxonomy, including three layers: socio-material entities, dimensions, and characteristics. Thereby, Figure 2 puts a clear structure to the collaborative interworking of human agents and AI-enabled systems. Using weak sociomateriality as justificatory knowledge, Research Article #1 presents AI-enabled systems and human agents as separate entities with distinct characteristics interacting globally to form socio-material practices. Bearing this in mind during the taxonomy development process, an integrated perspective on the complementary interworking of human agents and AI-enabled systems was taken. It follows that the taxonomy enables a well-founded classification of individual human-AI hybrids and creates a better understanding of what constitutes human-AI hybrids. Based on such a theoretically founded and empirically validated understanding of human-AI hybrids, this study complements existing research that structures specific aspects of human-AI collaboration and hybrid intelligence, such as tasks and interactions (Dellermann et al. 2019a; Dellermann et al. 2019b; Traumer et al. 2017).

Layer 1: Sociomaterial entities	Layer 2: Dimensions		Layer 3: Characteristics								
Human (human agency)	Human cognitive functions	NE	Perceiving	Reasoning	Predicting	Planning	Decision-making	Explaining	Interacting	Creating	Empathizing
	Interaction human to AI	ME	Facilitating	Verifying	Supplementing						
	Human focus	ME	Sensemaking	Creativity	Compassion	Flexibility					
AI (material agency)	AI cognitive functions	NE	Perceiving	Reasoning	Predicting	Planning	Decision-making	Interacting	Creating		
	Interaction AI to human	ME	Facilitating	Verifying	Supplementing						
	AI focus	ME	Automation	Augmentation							
Sociomaterial practices	Form of interworking	ME	Parallel	Sequential	Flexible						
	Mode of interworking	ME	Singular	Continuous							
	Learning	ME	None	AI learns	Human learns	Human and AI learn separately	Co-evolution				

ME = mutually exclusive, NE = non-exclusvie

Figure 2: Taxonomy of human-AI hybrids

To better understand the conceptualization of human-AI hybrids, Research Article #1 investigates whether there were any overarching interworking patterns across the classified hybrids. Based on the classification and analysis of 101 human-AI hybrids, the authors searched for archetypes of human-AI hybrids that outline the design opportunities that come with the collaborative interworking of human agents and AI-enabled systems. For this purpose, an agglomerative cluster analysis was applied, deriving five archetypes to conceptualize prototypical human-AI hybrid usage scenarios: sequential automation (*AI pre-worker)*, parallel automation (*outsourcing AI)*, sequential augmentation (*superpower-giving AI)*, sequential co-evolution (*assembly line AI)*, and flexible co-evolution (*collaborator AI)*. These archetypes provide a comprehensive picture of the possibilities available when human agents and AI-enabled systems engage in socio-material practices (s. Figure 3).

Each archetype represents a unique form of interworking, illustrated by analyzing an exemplary human-AI hybrid. Building on an extensive knowledge base, these archetypes offer insights into the prototypical implementation of human-AI hybrids in the real world. The taxonomy of human-AI hybrids also makes it possible to indicate differences in how closely human-AI hybrids are entangled in these archetypes. The analysis of relative frequencies and the correlation between different characteristics of human-AI hybrids reveals interesting dependencies, such as a link between the *interworking mode* and the *flexibility* requirement for human agents. Moreover, the study finds that an *AI-enabled system's focus* is connected to the *learning* possibilities. This work acknowledges the importance of both human and non-human agency, thus complementing existing research that focuses on specific use cases as well as predominantly social (e.g., Davenport et al. (2020), Maedche et al. (2019), Paschen et al. (2020), Rzepka and Berger (2018)) or technical aspects (e.g., Liew (2018), Østerlund et al. (2021)).

Human-AI Hybrids	Sociomaterial entities	Dimensions	Characteristics
Archetype 1 Sequential Automation (aka AI Pre-Worker)	Human (human agency)	Human cognitive functions	Reasoning/Decision-making (60%)
		Interaction human to AI	Supplementing (47%)
		Human focus	Sensemaking (73%)
	AI (material agency)	AI cognitive functions	Reasoning (93%)
		Interaction AI to human	Supplementing (73%)
		AI focus	Automation (100%)
	Sociomaterial practices	Form of interworking	Sequential (100%)
		Mode of interworking	Singular (100%)
		Learning	Human and AI learn separately (40%)
Archetype 2 Parallel Automation (aka Outsourcing AI)	Human (human agency)	Human cognitive functions	Reasoning/Interacting (48%)
		Interaction human to AI	Supplementing (61%)
		Human focus	Sensemaking (65%)
	AI (material agency)	AI cognitive functions	Reasoning (74%)
		Interaction AI to human	Supplementing (83%)
		AI focus	Automation (100%)
	Sociomaterial practices	Form of interworking	Parallel (43%)
		Mode of interworking	Continuous (100%)
		Learning	Human and AI learn separately (39%)
Archetype 3 Sequential Augmentation (aka Superpower-giving AI)	Human (human agency)	Human cognitive functions	Reasoning/Decision-making (59%)
		Interaction human to AI	Supplementing (82%)
		Human focus	Sensemaking (73%)
	AI (material agency)	AI cognitive functions	Reasoning (95%)
		Interaction AI to human	Facilitating (59%)
		AI focus	Augmentation (100%)
	Sociomaterial practices	Form of interworking	Sequential (100%)
		Mode of interworking	Singular (100%)
		Learning	Human learns (55%)
Archetype 4 Sequential Co-Evolution (aka the Assembly Line AI)	Human (human agency)	Human cognitive functions	Reasoning/Decision-making (62%)
		Interaction human to AI	Supplementing (86%)
		Human focus	Sensemaking (52%)
	AI (material agency)	AI cognitive functions	Reasoning (100%)
		Interaction AI to human	Facilitating (71%)
		AI focus	Augmentation (100%)
	Sociomaterial practices	Form of interworking	Sequential (100%)
		Mode of interworking	Continuous (100%)
		Learning	Co-evolution (43%)
Archetype 5 Flexible Co-Evolution (aka the Collaborator AI)	Human (human agency)	Human cognitive functions	Interacting (70%)
		Interaction human to AI	Supplementing (90%)
		Human focus	Flexibility (60%)
	AI (material agency)	AI cognitive functions	Reasoning (80%)
		Interaction AI to human	Faciliating/Supplementing (50%)
		AI focus	Augmentation (100%)
	Sociomaterial practices	Form of interworking	Flexible (85%)
		Mode of interworking	Continuous (100%)
		Learning	Co-evolution/Human learns (35%)

For each dimension, we illustrate the relative frequency of the characteristic which occurs most frequently

Figure 3: Archetypes of human-AI hybrids

2 Artifacts to Structure Smart Services and Derive Actionable Recommendations

2.1 Industrial Manufacturing: Predictive Maintenance as Promising Application of AI

Research Article #1 results implicate that human-AI hybrids play a pivotal role in the upcoming worksettings. Particularly in the service sector, combining the strengths of AI-enabled systems in processing data and generating insights with the unique qualities that humans (e.g., emphasizing and explaining) bring to service interactions is a promising approach. One example where human expertise complements the capabilities of AI-enabled systems is PdM. AI-enabled PdM systems can augment human inspectors in detecting upcoming machine failures and maintenance planning (Shin et al. 2021). As maintenance is one of the most significant cost drivers in the manufacuring sector, PdM is a value-promising application of AI in this sector (Windmark et al. 2018). Traditionally, maintenance strategies in the industrial context are either reactive or preventive. Data-based PdM approaches leverage collected data to analyze the fluctuation of system and process parameters and provide automatic signals if threshold values are exceeded (Bevilacqua and Braglia 2000). This approach involves, for example, using AI algorithms to predict upcoming failures and corresponding maintenance needs. In turn, maintenance cycles are optimized, which prevents breakdowns and reduces maintenance costs (Chen et al. 2019; World Economic Forum 2015).

Hitherto, statistical measures (e.g., absolute and relative measures) have been the paramount consideration in the selection and evaluation of PdM algorithms (e.g., Baptista et al. (2018)). In this context, statistical measures refer to the two types of prediction errors - alpha errors and beta errors. An alpha error means a machine runs as expected, but the algorithm falsely indicates an alarm. A beta error involves the algorithm ignoring a failure even though maintenance is required. The effects of alpha and beta errors on costs are unequal, as the two error types do not necessarily result in the same actions and costs. On the one hand, the costs of an ignored failure (beta error) and the resulting machine downtimes can vary considerably. In the case of a bottleneck machine, for example, a failure would affect the entire production line, resulting in high costs. On the other hand, the cost of an unnecessary check in response to a false alarm (alpha error) can also vary and may depend on technician density and availability in a specific sales territory, the cost of travel, and the type of check required. Consequently, in a sales territory with a very low service technician density or the case of a product with meager costs for machine downtimes, the cost resulting from an alpha error may be greater than the cost resulting from a beta error. This means that the statistical optimization of algorithms (e.g., a comparison based on relative error measures) will not necessarily lead to an economically favorable – or even economically viable – solution.

Alpha errors and beta errors may not be the only criteria (e.g., the type and granularity of the data and/or the algorithm's robustness may also have an influence), but they are essential factors in a decision. Hence, an economic trade-off between these two types of errors must be considered within any algorithm selection: If an algorithm is set to reduce the number of alpha errors, the number of beta errors will increase, et vice versa. This is because reducing the number of false alarms increases the probability of ignored failures. However, in a purely statistical perspective, the trade-off´s cost implications are neglected. In the industrial context, academics and practitioners – particularly FSPs – require support to select an economically viable option and optimize costs when introducing PdM as a means to leverage the potential of AI. Against this backdrop, Research Article #2 builds and evaluates a decision model that allows FPSs to prioritize economic concerns when selecting algorithms. In doing so, the decision model uses the underlying statistical foundation to translate into an economic perspective. For developing this decision model, Research Article #2 adopts the Design Science Research paradigm as established by Gregor and Hevner (2013), Hevner et al. (2004), and Jones and Gregor (2007). Sonnenberg and vom Brocke's (2012) evaluation guidelines were used to instantiate and evaluate this decision model. For instantiation and evaluation in a real-world setting, the case company is a European machinery company that builds and operates car wash systems.

The foundation for the decision model are the statistical error measures, i.e., the included statistical standard ratios for classification problems based on four decision model states, as explained in the following. The states contained in the decision model build on two *actual system states* ('failure', 'no failure') and two types of *algorithm predictions* ('alarm', 'no alarm'). Before a failure occurs, the algorithm can detect the failure (True positive) or miss the failure (False negative/beta error). If no failure occurs, the algorithm can falsely detect a failure (False positive/alpha error). If no failure is detected, the algorithm correctly does not indicate a failure (True negative).

The algorithms' prediction builds on data input through system observations. An observation could be a data point that can be classified (e.g., from previous experience with the system) as either incontrol or outcontrol. An observation classified as outcontrol means that a failure will occur within a specified time period following this observation, e.g., following a large deviation from a value in the normal state. An observation classified as incontrol means that no failure is predicted based on this observation since the observed value is in the normal state.

By applying an economic perspective, the decision model translates the prediction-based actions into the corresponding cost to reflect economic impacts (s. Table 1). This setup should enable our decision model's application in different PdM scenarios based on generic cost types meaningful to FSPs in the industrial context.

Table 1. Cost Implications of Decision Model States

Algorithm prediction / Actual system state	Alarm	No alarm
Failure	TC + CC + RC	TC + CC + RC + PC
No failure	TC + CC	No cost

Overall, the four decision model states and four cost types (travel cost (TC), check cost (CC), repair cost (RC), and penalty cost (PC)) lead to an observation cost function, which is linked to a time period-dependent observation function (e.g., seven days). First, if an observation is correctly detected as outcontrol, TC and CC for checking the failure and RC for repairing the system are incurred. Second, if the PdM algorithm does not detect a failure, PC needs to be considered in addition to TC, CC, and RC because service-level agreements are likely to have been breached. Third, if the PdM algorithm falsely indicates a failure, TC and CC, but no RC, will be incurred. Last, no cost will be incurred if the system runs as expected and no alarm is given. The cost for observations are calculated separately for each algorithm's prediction. By considering multiple time points sequentially, the four decision model states and four cost types lead to a total cost function that refers to the overall considered time period, adding up the corresponding observation cost. Optimizing the total cost function balances the trade-off between alpha errors and beta errors by considering the associated cost (i.e., TC, CC, RC, PC) to minimize the total cost for each algorithm. Then, to select the economically advantageous algorithm, the economically advantageous configuration (e.g., hyperparameter tuning) for each algorithm is selected for comparison among the set of algorithms. Finally, after comparing the total cost of the individual algorithms, the algorithm with the overall minimum total cost is to be selected from an economic perspective.

In order to identify an economically advantageous algorithm for PdM and prove the fidelity to the real world as well as the applicability of the decision model, sensor data from 4.9 million car wash cycles provided by the case company were analyzed. An exemplary subset of three algorithms was used to apply the decision model and select the economically advantageous algorithm. After comparing the total cost of the algorithms under consideration, the instantiation demonstrated that the decision model might lead to relevant cost savings (i.e., ~450,000 €, 17% compared to the second-best algorithm and more than 40% to reactive maintenance).

Research Article #2 contributes an artifact in the form of a decision model intending to support industrial companies that act as FSPs in selecting economically advantageous PdM algorithms. The authors rely on four generic cost components of FSPs to ensure the decision model is generalizable and transferable. These cost components (i.e., the specific value) can be determined individually for each case, offering applicability for a wide range of use cases. The case company confirmed the decision models' generalizability and transferred the decision model to other systems and failure types. Consequently, the decision model can also be applied in other industrial contexts and domains beyond the industrial context. An example for the applicability of the decision model could be the energy domain. For example, research in the energy domain examines PdM for wind farms (e.g., Florea et al. (2012), Vanden Haute and Pire (2020)) and should also consider economic factors.

2.2 The Potential of AI in the Context of Smart Energy Services

Understanding Smart Energy Services

Besides the potential of AI in the industrial manufacturing sector, numerous opportunities to utilize AI arise in the energy service sector. For example, the German government sees AI as a lever for mastering some of the most significant challenges of our time, such as climate change and pollution (The Federal Government of Germany 2020). AI is deemed for the transition to a more sustainable, reliable, intelligent energy ecosystem. This requires coordination and information sharing among various stakeholders, including utilities, grid operators, and consumers. Providing smart services in the energy sector can facilitate this coordination and enable vairous benefits (e.g., real-time communication, energy efficiency) (Paukstadt and Becker 2021a, 2021b; Paukstadt et al. 2019a). So called smart energy services (SES) are considered AI-based services in the energy sector (both residential and industrial) that provide a service based on data from a smart energy product (Paukstadt 2019; Paukstadt and Becker

2021b). However, given the important role of SES in driving a greener, smarter, and customer-centric energy transition, research hardly supports the design of SES (Paukstadt and Becker 2021a).

From an academic perspective, there is only a paucity of research supporting the development of SES, and there is still a lack of a holistic perspective that provides a structured overview of the heterogeneous nature of SES (Paukstadt and Becker 2021a). Most classifications and taxonomies consider smart services (e.g., Fischer et al. (2020), Knote et al. (2021), Paukstadt et al. (2019b)) or smart service systems in general (e.g., Beverungen et al. (2019), Brogt and Strobel (2020), Herterich et al. (2016)). Hitherto, SES has focused on the the application of SES in general (e.g., Matschoss and Kahma (2015), Matschoss et al. (2015)) and on SES business models (e.g., Chasin et al. (2020a), Paukstadt and Becker (2021b), Paukstadt et al. (2019a)). In addition, some frameworks refer to the research context of smart city services, only limited considering energy services, as research on smart cities has a deviating but cross-cutting focus with SES (e.g., Benites and Simões (2021), Lee and Lee (2014), Pourzolfaghar and Helfert (2017)). Two frameworks offer partially structural insights (i.e., Paukstadt (2019) and Paukstadt and Becker (2021b)), but do not address the aforementioned lack of a structured approach for describing SES in their heterogenous nature. To that end, there is specific research on SES, but a structuring approach for SES in general is missing.

However, an understanding of the essential characteristics of SES is important to understand how an SES can be built and developed to suit the market and customers. This is especially relevant as service providers and service innovators (e.g., business development and start-ups) still are facing challenges developing, and deploying purposeful SES (Bennett et al. 2021). There is a high failure-rate of green start-ups in delivering the expected outcomes and meeting investors expectations with over 80% of failed or cheaply sold start-ups (Bennett et al. 2021). A standardized, detailed, and structured description of the essential characteristics of SES can help to create a common and sound knowledge base to classify and describe the heterogeneous nature of SES. Among other things, a structured description enables organized thinking for the innovation process and can serve as a tool for market analysis (i.e., one can classify existing SES and identify market gaps) by shedding light on the facets of SES and providing an unbiased interpretation of the characteristics. Against this background, Research Article #3 proposes a taxonomy of SES based on the established procedure by Kundisch et al. (2021) and Nickerson et al. (2013). The taxonomy is derived from existing conceptualizations in literature, analyzing existing SES, and evaluated with five interviews by experts from practice and science.

The taxonomy includes four layers: Structure, Value Creation, Delivery, and Energy-related Data Input. It comprises four distinct SES entities: (1) the structuring of a service in the energy domain itself, (2) the characteristics of how the service creates value, (3) the way the service delivers the value, and (4) the fundamental characteristics of the SES's data. Each layer contains four dimensions, except delivery with three dimensions, resulting in a total of 15 dimensions, eight of which are mutually exclusive (ME) and seven of which are non-exclusive (NE) (see Figure 4).

With this structure, the taxonomy provides a descriptive, structuring approach to the relatively new and heterogeneous field of SES. Drawing on the understanding of SES, an integrated perspective on the complementary construction of SES was taken when developing the taxonomy. As a result, the taxonomy enables a well-founded classification of individual SES and deepens the understanding of what specifically characterizes SES. Based on such a theoretically grounded and empirically validated understanding of SES, the study complements existing research that structures specific aspects of smart services and energy services (e.g., Fischer et al. (2020), Paukstadt and Becker (2021b), Paukstadt et al. (2019b)).

	Dimension	ME	Characteristics					
Structure	*Main Purpose for Smart Energy Service Provider*	Y	Financial Value	Environmental Value	Functional Value			
	Main Purpose for Energy Consumer	Y	Financial Value	Environmental Value	Functional Value			
	Additional Stakeholders & Participants	N	Governing Institutions	Focal Company	Community	None		
	Energy Consumer	Y	Industry	Retail	Residential			
Value Creation	*Benefit*	Y	Efficiency Gain	Improved Function	New Offering			
	Types of Value Gain	Y	Value-in-Use	Value-in-Exchange				
	Functions	Y	Data Digitization & Connectivity	Monitoring & Reporting	Notification & Alerting	Recommending & Optimizing	Autonomous Acting	Decision Supporting
	Source of Energy Consumption	N	Light	HVAC	Powering			
Delivery	*Pricing Model*	Y	Transaction-based	Subscription-based	Hybrid	Free		
	Service Interaction	Y	Energy Consumer Active	Smart Energy Service Provider Active	Interactive	Machine Active		
	Sales Channel	N	B2B	B2C	Intermediary			
Energy-related Data Input	*Data Provider*	N	Energy Consumer	Smart Energy Service Provider	Third Party			
	Data Type	N	Energy Demand & Generation	(Energy) Market Data	Grid Data	Sustainability Data	Meteorological Data	Building Data
	Data Time Horizon	N	Historical	Present	Forecast			
	Data Collection	N	Continous	On-demand	Event-triggered			

ME = mutually exclusive, Y = yes, N = no

Figure 4: Taxonomy of SES

The taxonomy connects to and advances the discourse on SES and future work in IS, business development, and energy research (e.g., Beverungen et al. (2019), Chasin et al. (2020a), Chasin et al. (2020b), Paukstadt and Becker (2021b)). In this regard, our taxonomy adds descriptive knowledge to the field of SES by describing them in a detailed and structured way. In this vein, the taxonomy supports practice-oriented research as well as service providers and innovators in the more efficient use and development of value-creating SES in the future. Furthermore, the taxonomy enables research and practice to group existing SES into a taxonomy based on common characteristics and clarify their relationships based on their characteristics (Cook et al. 1999; Nickerson et al. 2013). Because SES are a new and rapidly evolving phenomenon, there is less support for analyzing existing services and developing new smart service offerings. Therefore, Research Paper #3 contributes a solid basis for identifying SES characteristics as a starting point for further investigation through research and practice. Consequently, it answers the calls of IS and the energy sector research (e.g., Paukstadt and Becker (2021a)) for a structuring approach to SES and lays a foundation for further developments like business models for SES.

Business Model Perspective on NILM as a Smart Energy Services

The industrial sector is motivated to reduce energy consumption due to rising prices, threatening competitiveness (Rusche et al. 2021). Additional economic pressure comes from the volatile electricity supply, resulting in fluctuating energy prices (Scheubel et al. 2017). Therefore, energy efficiency and flexibility are increasingly vital to counter rising economic pressure and get management's attention (Bauer et al. 2021; Glenk et al. 2021; Paukstadt and Becker 2021b).

One promising SES to foster energy efficiency and flexibility is NILM. NILM identifies individual consumers (i.e., energy-consuming devices) in an aggregated power consumption load profile measured from a single meter (Ruano et al. 2019). Each device generates a load profile that suitable algorithms can identify and classify. Thus, NILM enables transparency of energy consumption (Barth et al. 2018; Bergman et al. 2011; Gopinath et al. 2020). Consumption transparency, in turn, is required for energy efficiency and flexibility using energy management systems (Lindner et al. 2021; Seow and Rahimifard 2011). For instance, transparency allows monitoring the overall condition of appliances and enables identifying inefficient operating modes or imminent failures to take predictive measures to reduce efficiency losses and downtime. NILM is already used in many private households. However, industrial NILM service providers are rare (Kalinke et al. 2021). Furthermore, research on

NILM in industrial applications almost exclusively investigates technical aspects, such as optimizing different algorithms to achieve higher accuracy and identify appliances more accurately. In other words, there is a gap between technically oriented research and applying NILM in practice, although it would be promising for energy efficiency and flexibility. Therefore, to leverage the business potential of NILM in a manufacturing environment, a business model framework that enables structuring and developing a business model for NILM in industrial applications is needed. Therefore, Research Article #4 adapts the Design Science Research Approach following Hevner (2007) and Jones and Gregor (2007) for building and evaluating an artifact - the Smart Co-Creation Service Canvas (SCSC).

The SCSC enables the structuring and development of a business model for NILM in the industrial sector. Research Article #4 is divided into three main steps. First, it analyzes the knowledge base in step one by conducting a literature review. This knowledge base is enriched with the author’s experience and expertise gained in (research) projects to have a solid basis for developing the SCSC. This step allows us to derive 59 hypotheses for the SCSC.

Second, Research Article #4 incorporates requirements from the contextual environment to verify and evaluate the artifact. Given the complexity of a business model with its many elements and the still rudimentary state of research on industrial NILM applications and their practical relevance, expert interviews are used for evaluation.

The SCSC (see Figure 5) is developed based on the evaluation of 59 hypotheses through expert interviews. The SCSC contains nine interrelated elements relevant to SES for a holistic framework: customer segments, value proposition, value creation, key resources, technical infrastructure and digital platform, interaction and co-production, cost structure, revenue streams, and key partners.

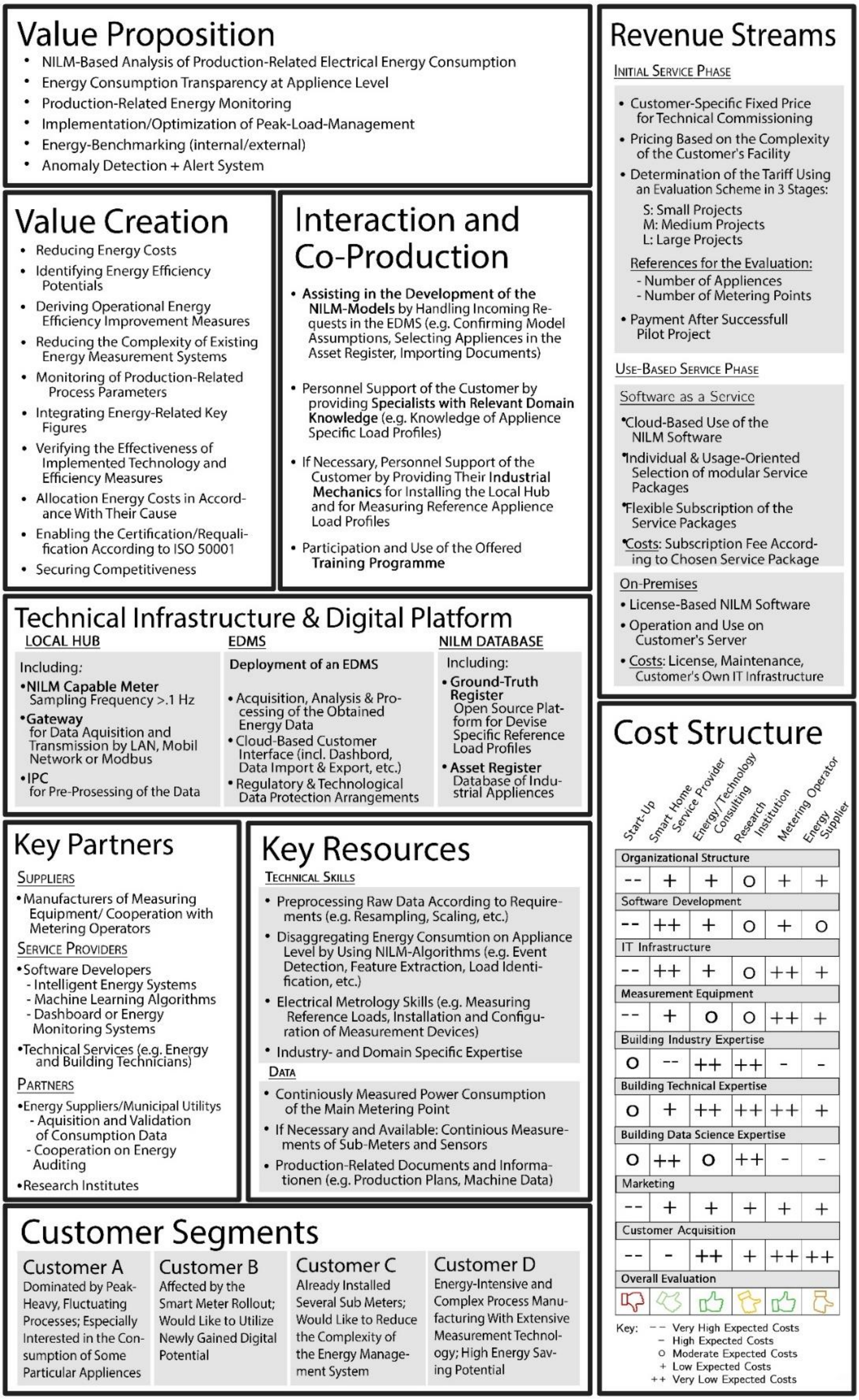

Figure 5: Empirically verified and revised elements of the SCSC

With this setup, the SCSC allows interdisciplinary solutions and leveraging technical and economic potentials, merging previously separate research streams. In this vein, the SCSC provides holistic guidance for business model development for NILM. Therefore, the SCSC offers a business perspective on NILM as an applicable, realistic, and practical model, which is confirmed by the experts (Sonnenberg and vom Brocke 2012). Following the business perspective, the SCSC provides a twofold view, examining the customer and provider sides of co-creating value and monetizing SES. As the interviews confirmed, monetizing SES is crucial. However, especially for SES, there is hardly any guidance. Existing works are mostly limited to payment/rate models without further details (e.g., Paukstadt and Becker (2021b)). However, it is crucial to quantify the economic potential individually, especially for SES in the industrial context, which encounters highly individual applications. This builds customer trust and creates a profitable business model, which is the basis for customer-centric pricing. Hence, the SCSC provides insights and information on revenue streams and cost structure.

In sum, Research Article#4 contributes to the prescriptive knowledge of SES, in general, and NILM-based services in the industrial sector. Since the SCSC brings an economic perspective to what is otherwise a primarily technical and computer science-oriented area of the literature, the SCSC guides implementing a NILM-based business model.

Understanding Data Challenges when Designing Purposeful SES

As Research Article#4 shows, NILM-based services are promising and cost-effective approaches that incorporate techniques that infer individual applications' energy consumption from aggregated consumption. These solutions enable smart energy management and transparency on energy consumption data and are needed to enforce energy efficiency. Use cases of NILM include energy monitoring, demand side management, peak shaving, job scheduling, as well as anomaly and fault detection for saving energy (Barth et al. 2018; Bergman et al. 2011; Gopinath et al. 2020). For example, early detection of those faults or anomalies with the help of NILM avoids economic, energy, and environmental losses due to, e.g., maintenance cost reduction, machine fault reduction, increased spare part life, or the identification of inefficient applications (Gopinath et al. 2020). However, although NILM has existed for decades, the primary application area of NILM is smart energy monitoring in the residential sector (Langevin et al. 2022; Verma et al. 2021; Zhou et al. 2021) while it has not been widely adopted in industrial applications (Cui et al. 2022; Gopinath et al. 2020; Holmegaard and Baun Kjaergaard 2016). A fundamental problem is the lack of industrial data labels as input for effective supervised algorithms (Feng and Tian 2021). Nevertheless, labeling new data in an industrial environment requires domain-specific knowledge, is time-consuming and expensive to obtain and is often unattractive in practice (Feng and Tian 2021; Yu et al. 2021). Labeling in the context of NILM means determining the disaggregated applications from the total electrical energy consumption and to what extent they were used at the given timestamp.

Consequently, Research Article #5 aims to reduce labeling efforts using active learning. Active learning is a machine learning approach in which experts query the unlabeled data with the highest level of informativeness to provide targeted feedback to the learning algorithm to improve its performance (Das et al. 2016; Mehrotra et al. 2017). The concept of active learning is applied in various disciplines (Angelis et al. 2022; Das et al. 2016; Kumar and Gupta 2020; Ren et al. 2022). In the context of NILM, the labeled data is used for training the disaggregation algorithms that predict the energy consumption of the individual applications. In other domains besides NILM, previous research has shown the potential of active learning to reduce the labeling effort (Rožanec et al. 2022; van Leeuwen and Koole 2023; Zhao et al. 2022). Therefore, Research Article #5 integrates an active learning model into NILM for industrial applications. Reducing the labeling effort, especially in an industrial environment, increases the attractiveness of NILM. This enables smart energy management and favors companies ecologically and economically. Research Article #5 develops an active learning model using the HIPE data set based on a real-world production plant (Bischof et al. 2018). It implements the model to validate the underlying concept of reducing the labeling effort. The methodology is based on the Cross-Industry Standard Process for Data Mining (CRISP-DM). The proposed model does not replace existing NILM techniques. Instead, it complements its techniques by significantly reducing data labeling and user effort while maintaining appropriate disaggregation accuracies. This reduces concerns about the cost of NILM and supports intelligent energy management based on the transparency provided. To demonstrate its performance, the active learning model is compared with established supervised learning models in NILM systems for industrial applications.

The results show that the present active learning model can effectively reduce the labeling effort for NILM by up to 99% while still achieving up to 80% of the prediction performance compared to a benchmark with 100% labeled training data. The design of the active learning model consists of an unsupervised model, a feedback module, and a supervised model. Research Article #5 also provides a sensitivity analysis to demonstrate the impacts of different parameter settings (i.e., different budget constraints for the feedback module). In active learning, budget refers to limited resources, often labeled examples, that can be used to train the active learning model (Das et al. 2016). The results show that the designed active learning model leads to a more cost-effective NILM system in practice. In addition to the possibility of using easily collected energy consumption data, the expert system combined with human annotators can be efficiently used to further optimize the active learning model on the specific industry and use case.

The presented active learning architecture reduces the labeling effort, mitigating one of the critical barriers to adopting NILMs in industrial applications. For example, practitioners could use NILM for failure prediction, leading to cost savings and increased equipment efficiency, or for emission reduction and energy savings through smarter energy management (Beverungen et al. 2019). Consequently, more expansive use of NILM could help practitioners save energy and costs and contribute to cleaner and more sustainable production. Therefore, Research Article #5 concludes that the proposed active learning could be a viable alternative to traditional submetering, although it has deficits in disaggregation compared to established supervised learning models. The significant time and resource savings compensate for this shortcoming.

III Summary and Limitations

1 Summary

AI offers promising opportunities believed to contribute to the well-being of individuals, the success and innovation of businesses, and the prosperity and progress of society (Thiebes et al. 2021). The powerful combination of AI and humans is expected to deliver new, value-generating smart services. However, many organizations face challenges in realizing the value of using AI (Ransbotham et al. 2020). Motivated by these circumstances, this doctoral thesis aims to reduce the barriers to *designing purposeful smart services* by a twofold approach: On the one hand, an integrative perspective on *understanding human-AI hybrids as the foundation for smart services* is taken to understand better the nature of human-AI hybrids and analyze their range of roles in depth. Therefore, this doctoral thesis deepens our understanding of the entanglement between human agents and AI-enabled systems. In this vein, it provides a taxonomy to identify human-AI hybrids' characteristics and structure them. Furthermore, it identifies archetypes of human-AI hybrids by investigating ideal-typical occurrences of human-AI hybrids in practice. On the other hand, this doctoral thesis aims to contribute to the challenges above by developing *artifacts to structure smart services and derive actionable recommendations* for designing purposeful smart services. Doing so, this doctoral thesis provides insights into the design of smart services in the industrial manufacturing and energy service sectors, providing several artifacts: an economic decision-support model for PdM for FSPs, a taxonomy to characterize and structure SES, a business model framework for SES, and an active learning model to reduce labeling efforts for NILM as specific SES. Consequently, it provides practical and empirically validated artifacts to support structuring and designing smart services.

Concerning the *understanding of human-AI hybrids as the foundation for smart services*, Section II.1 provides an overview of the characteristics and archetypes that practitioners and academics deem relevant when companies use AI. Furthermore, it investigates the transformation of the interworking of humans and AI-enables systems (Research Article #1). Drawing from weak sociomateriality as justificatory knowledge, Section II.1 provides a holistic understanding of the entangled interworking of human-AI hybrids. Therefore, this doctoral thesis provides a new, balanced perspective that accounts for the complementary attributes and capabilities of human agents and AI-enabled systems in equal measure to foster their collaborative interworking. Based on this perspective, the identified five archetypes of human-

AI hybrids outline the design opportunities that come with the interworking of human agents and AI-enabled systems.

Concerning *artifacts to structure smart services and derive actionable recommendations for designing purposeful smart services*, Section II.2 provides a quantitative decision-support model that assists decision-makers in choosing the economically favorable algorithm for their PdM services based on their underlying cost structure (Research Article #2). The decision support models' applicability was instantiated and evaluated in a real-world setting with a European machinery company providing full-service solutions for car wash systems. The instantiation uses its customers' data, i.e., the data of large petrol station chains, to demonstrate the decision model's applicability and effectiveness with fidelity to a real-world phenomenon. In sum, the decision model provides economic insights into the trade-off between the algorithms' error types and enables users to focus on economic concerns in algorithm selection. The work contributes to the prescriptive knowledge of algorithm selection and predictive maintenance in line with considering different types of costs.

Section II.3 provides a new theoretical foundation on the characteristics of SES. This new theoretical foundation provides a taxonomy of four entities and 15 dimensions (Research Article #3). The taxonomy supports researchers and practitioners in describing and analyzing the essential characteristics of SES and offers a theoretically and empirically validated foundation. In this vein, the taxonomy provides a descriptive, structuring approach to the essential characteristics of SES and helps to analyze, and identify different possible SES and their configuration options. Building on this understanding of SES, a business model framework – the SCSC - is provided to structure and support the development of a business model for NILM (Research Article #4). The SCSC is a practical and strategic framework for concretizing and implementing a business idea to complement the ongoing, mainly technological-focused research activities. Since the SCSC brings an economic perspective to what is otherwise a primarily technical and computer science-oriented area of the literature, it guides implementing a business model for NILM. Furthermore, the doctoral thesis developed an active learning model using real-world data and compared three disaggregation algorithms with a benchmark model by efficiently selecting a subset of training data (Research Article #5). The approach demonstrates that the active learning model achieves satisfactory accuracy with highly reduced user input. This model aims to overcome the critical challenge of NILM in industrial applications: the scarcity of labeled data, which leads to costly and time-consuming workflows. In this vein, this model lays the foundation for further optimizations regarding the architecture of an active learning model and serves as a first benchmark for active learning in NILM for industrial applications. With these three research articles, this doctoral thesis contributes to reducing barriers through practical and empirically validated artifacts and recommendations for designing purposeful SES.

2 Limitations and Future Research

The results of this doctoral thesis have limitations that provide an impetus for future research endeavors. This section provides an overview of these limitations, resulting in future avenues for scholars that examine the interworking of humans and AI in general and the implications of the design of smart services. Furthermore, the individual research articles provide a detailed perspective on the limitations of this research endeavor and their potential for future research (see the Appendix section).

First, the developed taxonomies of Research Articles #1 and #3 have demonstrated the potential to deepen the understanding of human-AI hybrids and SES. However, the inherently descriptive nature of a taxonomy limits the extent of guidance and insights they can give. The development of taxonomies requires a certain extent of generalization and simplification of complex issues. Consequently, these generalizations and simplifications inevitably limit our findings from both analyses. However, further research (e.g., in-depth case studies) could provide the additional insights needed to tease out interdependencies of characteristics not captured by the two taxonomies. Furthermore, as the deployment of human-AI hybrids and SES is still in its infancy, more elaborate use cases of human-AI hybrids and SES are likely to emerge. These projected advances may require specific changes to the proposed dimensions or extensions of the taxonomies. Therefore, the developed taxonomies should not be considered as a completed artifact but as a basis for further research to review and revise the taxonomies at appropriate intervals.

Second, Research Articles #2, #4, and #5 must also make simplifiying assumptions. Research Article #2 has to break down a complex cost structure into four generic cost types. For example, penalty costs can differ from customer to customer, as can travel costs, which are only considered in terms of averages in the decision model. Also, the cost could be staggered in reliance of, e.g., working time, customer types, or service level agreements. Research Article #4 did not address the technical aspects to the extent that might have been necessary to provide a practical solution for a primarily technology-oriented business idea. However, both artifacts are designed to be generic and transferable. Therefore, both artifacts provide an opportunity for further development and application in future research, e.g., in the form of (multiple) case studies in other companies, countries, and industries. In Research Article #5, by design, active learning models assume that the expert system is infallible. This assumption may differ in many real-world situations, especially when a human is involved in labeling. Hence, to increase the feasibility of the active learning model, future research could sprinkle random misjudgments. Alternatively, a proactive learning model could be proposed instead of adding randomness, as it is a generalization of active learning with the purpose of reducing idealistic assumptions. Therefore, it could bridge the gap between traditional active learning and more suitable real-world applications.

Third, the developed artifacts in the Research Articles #1, #2, #3, and #4 were evaluated by external experts. These experts were carefully selected to relate as closely as possible to the topic, with the goal of covering a broad but relevant range of opinions and experiences. However, bias cannot be ruled out as these are only random samples. Most experts are familiar with working in international and globally operating companies and can provide a broad assessment. In principle, further evaluations with more experts would be conceivable. For example, evaluating the artifacts by groups of experts divided by region could provide interesting insights and enable a comparison (e.g., concerning regional characteristics).

Fourth, the used data is a limitation for Research Articles #2 and #5. Since data plays an essential role in the algorithms, the accessibility, structure, and quality of data affect the predictive performance. This, in turn, directly affects the predicted cost of the decision support model in Research Article #2. The DM's instantiation focus is restricted to one case company and limited to one specific failure type and one sensor. Further research should consider more sensor data and the interaction between sensors and the environment. A broader data set, including environmental data (e.g., meteorological data), will allow for sophisticated prediction variants, e.g., in the case of predicting special environmental pollution (e.g., Sahara dust) and thus extraordinary wear of machine parts. By adding more sensors and machine parts, combined maintenance planning across multiple components and taking into account economic factors (e.g. synergies in maintenance planning) is also possible. For Research Article #5, the proposed active learning model was validated on a single data set containing only ten applications covering one power-electronics plant. This limitation must be overcome in further research with more data sets and a broader application scenario (e.g., more plants).

In summary, the application of AI is driving the pace of change in many industries, transforming human-AI collaboration and bringing new opportunities for business models, especially in the service domain. By providing insights into existing opportunities and challenges, I sincerely hope that this dissertation will help researchers and practitioners explore the changes brought about by the powerful interaction of humans and AI. Furthermore, I hope it will support researchers and pracitioners in the design of purposeful smart services.

IV References

Ågerfalk PJ (2020) Artificial intelligence as digital agency. European Journal of Information Systems 29(1):1–8. doi:10.1080/0960085X.2020.1721947.

Agrawal A, Gans J, Goldfarb A (2018) Prediction machines: The simple economics of artificial intelligence, Boston, Massachusetts.

Ahmad T, Zhu H, Zhang D, Tariq R, Bassam A, Ullah F, AlGhamdi AS, Alshamrani SS (2022) Energetics Systems and artificial intelligence: Applications of industry 4.0. Energy Reports 8:334–361. doi:10.1016/j.egyr.2021.11.256.

Al-Antari MA (2023) Artificial Intelligence for Medical Diagnostics-Existing and Future AI Technology! Diagnostics (Basel, Switzerland) 13(4). doi:10.3390/diagnostics13040688.

Angelis G-F, Timplalexis C, Krinidis S, Ioannidis D, Tzovaras D (2022) NILM applications: Literature review of learning approaches, recent developments and challenges. Energy and Buildings 261:111951. doi:10.1016/j.enbuild.2022.111951.

Anke J, Ebel M, Poeppelbuss J, Alt R (2020) How to tame the Tiger - Exploring the Means, Ends and Challenges in Smart Service Systems Engineering. In Proceedings of the 28th European Conference on Information Systems (ECIS).

Baptista M, Sankararaman S, Medeiros IP de, Nascimento C, Prendinger H, Henriques EM (2018) Forecasting fault events for predictive maintenance using data-driven techniques and ARMA modeling. Computers & Industrial Engineering 115:41–53. doi:10.1016/j.cie.2017.10.033.

Barth L, Hagenmeyer V, Ludwig N, Wagner D (2018) How much demand side flexibility do we need? In: Proceedings of the Ninth International Conference on Future Energy Systems. ACM, New York, NY, USA, pp 43–62.

Bauer D, Hieronymus A, Kaymakci C, Köberlein J, Schimmelpfennig J, Wenninger S, Zeiser R (2021) Wie IT die Energieflexibilitätsvermarktung von Industrieunternehmen ermöglicht und die Energiewende unterstützt. HMD Praxis der Wirtschaftsinformatik 58(1):102–115. doi:10.1365/s40702-020-00679-8.

Benbya H, Pachidi S, Jarvenpaa SL (2021) Special Issue Editorial: Artificial Intelligence in Organizations: Implications for Information Systems Research. Journal of the Association for Information Systems 22(2):281–303. doi:10.17705/1jais.00662.

Benites AJ, Simões AF (2021) Assessing the urban sustainable development strategy: An application of a smart city services sustainability taxonomy. Ecological Indicators 127:107734. doi:10.1016/j.ecolind.2021.107734.

Bennett S, Le Marois J-B, Orgland N (2021) Ten years of clean energy start-ups: Tracking success and looking ahead to opportunities in emerging markets.

Berente N, Gu B, Recker J, Santhanam R (2021) Managing Artificial Intelligence. MIS Quarterly 45(3):1433–1450. doi:10.25300/MISQ/2021/16274.

Bergman D, Jin D, Juen J, Tanaka N, Gunter C, Wright A (2011) Nonintrusive Load-Shed Verification. IEEE Pervasive Computing 10(1):49–57. doi:10.1109/MPRV.2010.71.

Beverungen D, Müller O, Matzner M, Mendling J, vom Brocke J (2019) Conceptualizing smart service systems. Electronic Markets 29(1):7–18. doi:10.1007/s12525-017-0270-5.

Bevilacqua M, Braglia M (2000) The analytic hierarchy process applied to maintenance strategy selection. Reliability Engineering & System Safety 70(1):71–83. doi:10.1016/S0951-8320(00)00047-8.

Bischof S, Trittenbach H, Vollmer M, Werle D, Blank T, Böhm K (2018) HIPE. In: Proceedings of the Ninth International Conference on Future Energy Systems. ACM, New York, NY, USA, pp 599–603.

Brogt T, Strobel G (2020) SERVICE SYSTEMS IN THE ERA OF THE INTERNET OF THINGS: A SMART SERVICE SYSTEM TAXONOMY. Proceedings of the 28th European Conference on Information Systems (ECIS).

Bughin J, Seong J, Manyika J, Chui M, Joshi R (2018) Notes from the AI frontier: Insights from hundreds of use cases. https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-applications-and-value-of-deep-learning. Accessed 2022-01-03.

Bundesministerium für Wirtschaft und Energie (BMWi) (2019) Geschäftsmodellentwicklung in der Smart Service Welt, Berlin.

Chasin F, Paukstadt U, Gollhardt T, Becker J (2020a) Smart energy driven business model innovation: An analysis of existing business models and implications for business model change in the energy sector. Journal of Cleaner Production 269:122083. doi:10.1016/j.jclepro.2020.122083.

Chasin F, Paukstadt U, Ullmeyer P, Becker J (2020b) Creating Value From Energy Data: A Practitioner's Perspective on Data-Driven Smart Energy Business Models. Schmalenbach Business Review 72(4):565–597. doi:10.1007/S41464-020-00102-1.

Chen C, Liu Y, Sun X, Di Cairano-Gilfedder C, Titmus S (2019) Automobile Maintenance Prediction Using Deep Learning with GIS Data. Procedia CIRP 81:447–452. doi:10.1016/j.procir.2019.03.077.

Cook DP, Goh C-H, Chung CH (1999) SERVICE TYPOLOGIES: A STATE OF THE ART SURVEY. Production and Operations Management 8(3):318–338. doi:10.1111/j.1937-5956.1999.tb00311.x.

Cui J, Jin Y, Yu R, Okoye MO, Li Y, Yang J, Wang S (2022) A robust approach for the decomposition of high-energy-consuming industrial loads with deep learning. Journal of Cleaner Production 349:131208. doi:10.1016/j.jclepro.2022.131208.

Das S, Wong W-K, Dietterich T, Fern A, Emmott A (2016) Incorporating Expert Feedback into Active Anomaly Discovery. In: 2016 IEEE 16th International Conference on Data Mining (ICDM). IEEE, pp 853–858.

Daugherty PR, Wilson HJ (2018) Human + machine: Reimagining work in the age of AI. Harvard Business Review Press, Boston, MA.

Davenport TH (2018) The AI Advantage: How to put the artificial intelligence revolution to work. The MIT Press, Cambridge, MA.

Davenport TH, Guha A, Grewal D, Bressgott T (2020) How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science 48(1):24–42. doi:10.1007/s11747-019-00696-0.

Davenport TH, Ronanki R (2018) Artificial intelligence for the real world. Harvard Business Review 96(1):108–116.

Dellermann D, Calma A, Lipusch N, Weber T, Weigel S, Ebel P (2019a) The Future of Human-AI Collaboration: A Taxonomy of Design Knowledge for Hybrid Intelligence Systems. In: Proceedings of the 52nd Hawaii International Conference on System Sciences, Maui, HI.

Dellermann D, Ebel P, Söllner M, Leimeister JM (2019b) Hybrid Intelligence. Business & Information Systems Engineering 61(5):637–643. doi:10.1007/s12599-019-00595-2.

Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, …, Williams MD (2021) Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management 57:101994. doi:10.1016/j.ijinfomgt.2019.08.002.

European Commission (2020) COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS: Stepping up Europe's 2030 climate ambition. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:52012DC0673:EN:NOT

Feng C, Tian P (2021) Time Series Anomaly Detection for Cyber-physical Systems via Neural System Identification and Bayesian Filtering. In: Zhu F (ed) Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining. Association for Computing Machinery, New York,NY,United States, pp 2858–2867.

Fischer M, Heim D, Hofmann A, Janiesch C, Klima C, Winkelmann A (2020) A taxonomy and archetypes of smart services for smart living. Electronic Markets 30(1):131–149. doi:10.1007/s12525-019-00384-5.

Flavián C, Pérez-Rueda A, Belanche D, Casaló LV (2022) Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness. Journal of Service Management 33(2):293–320. doi:10.1108/JOSM-10-2020-0378.

Florea G, Paraschiv A, Cimpoeşu E (2012) Wind Farm Noise Monitoring Used for Predictive Maintenance. IFAC Proceedings Volumes 45(6):1822–1827. doi:10.3182/20120523-3-RO-2023.00435.

Fügener A, Grahl J, Gupta A, Ketter W (2021) Will Humans-in-the-Loop Become Borgs? Merits and Pitfalls of Working with AI. MIS Quarterly 45(3):1527–1556. doi:10.25300/MISQ/2021/16553.

Gaskin J, Berente N, Lyytinen K, Yoo Y (2014) Toward Generalizable Sociomaterial Inquiry: A Computational Approach for Zooming In and Out of Sociomaterial Routines. MIS Quarterly 38(3):849–871. doi:10.25300/MISQ/2014/38.3.10.

Geissdoerfer M, Vladimirova D, Evans S (2018) Sustainable business model innovation: A review. Journal of Cleaner Production 198:401–416. doi:10.1016/j.jclepro.2018.06.240.

Glenk G, Meier R, Reichelstein S (2021) Cost Dynamics of Clean Energy Technologies. Schmalenbach Journal of Business Research:1–28. doi:10.1007/s41471-021-00114-8.

Gopinath R, Kumar M, Prakash Chandra Joshua C, Srinivas K (2020) Energy management using non-intrusive load monitoring techniques – State-of-the-art and future research directions. Sustainable Cities and Society 62:102411. doi:10.1016/j.scs.2020.102411.

Gregor S, Hevner AR (2013) Positioning and Presenting Design Science Research for Maximum Impact. MIS Quarterly 37(2):337–355. doi:10.25300/MISQ/2013/37.2.01.

Herterich MM, Buehnen T, Uebernickel F, Brenner W (2016) A Taxonomy of Industrial Service Systems Enabled by Digital Product Innovation. In: 2016 49th Hawaii International Conference on System Sciences (HICSS). IEEE, pp 1236–1245.

Heuchert M, Verhoeven Y, Cordes A, Becker J (2020) Smart Service Systems in Manufacturing: An Investigation of Theory and Practice. Hawaii International Conference on System Sciences.

Hevner AR (2007) A Three Cycle View of Design Science Research. Scandinavian Journal of Information Systems. Vol. 19(2):87–92.

Hevner AR, March ST, Park J, Ram S (2004) Design Science in Information Systems Research. MIS Quarterly 28(1):75–105.

Holmegaard E, Baun Kjaergaard M (2016) NILM in an Industrial Setting: A Load Characterization and Algorithm Evaluation. In: 2016 IEEE International Conference on Smart Computing (SMARTCOMP). IEEE, pp 1–8.

Jarrahi MH (2018) Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons 61(4):577–586. doi:10.1016/j.bushor.2018.03.007.

Jones D, Gregor S (2007) The Anatomy of a Design Theory. Journal of the Association for Information Systems 8(5):312–335. doi:10.17705/1jais.00129.

Kalinke F, Bielski P, Singh S, Fouché E, Böhm K (2021) An Evaluation of NILM Approaches on Industrial Energy-Consumption Data. Proceedings of the Twelfth ACM International Conference on Future Energy Systems:239–243. doi:10.1145/3447555.3464863.

Kautz K, Jensen TB (2013) Sociomateriality at the royal court of IS. Information and Organization 23(1):15–27. doi:10.1016/j.infoandorg.2013.01.001.

Klein MM, Biehl SS, Friedli T (2018) Barriers to smart services for manufacturing companies – an exploratory study in the capital goods industry. Journal of Business & Industrial Marketing 33(6):846–856. doi:10.1108/JBIM-10-2015-0204.

Knote R, Janson A, Söllner M, Leimeister JM (2021) Value Co-Creation in Smart Services: A Functional Affordances Perspective on Smart Personal Assistants. Journal of the Association for Information Systems 22(2):418–458. doi:10.17705/1jais.00667.

Kratochwill, Lisa, Richard P, Babilon L, Rehmann F, Mamel S, Fasbender S (2020) Artificial Intelligence – from Hype to Reality for the Energy Industry: An in-depth analysis of fields of application for AI in the energy industry, Berlin.

Kumar P, Gupta A (2020) Active Learning Query Strategies for Classification, Regression, and Clustering: A Survey. Journal of Computer Science and Technology 35(4):913–945. doi:10.1007/s11390-020-9487-4.

Kundisch D, Muntermann J, Oberländer AM, Rau D, Röglinger M, Schoormann T, Szopinski D (2021) An Update for Taxonomy Designers. Business & Information Systems Engineering. doi:10.1007/s12599-021-00723-x.

Langevin A, Carbonneau M-A, Cheriet M, Gagnon G (2022) Energy disaggregation using variational autoencoders. Energy and Buildings 254:111623. doi:10.1016/j.enbuild.2021.111623.

Larson RC (2016) Commentary—Smart Service Systems: Bridging the Silos. Service Science 8(4):359–367. doi:10.1287/serv.2016.0140.

Lee J, Lee H (2014) Developing and validating a citizen-centric typology for smart city services. Government Information Quarterly 31:S93-S105. doi:10.1016/j.giq.2014.01.010.

Lee KP, Chng CW, Tong DL, Tseu KL (2023) Optimizing Energy Consumption on Smart Home Task Scheduling using Particle Swarm Optimization. Procedia Computer Science 220:195–201. doi:10.1016/j.procs.2023.03.027.

Liew C (2018) The future of radiology augmented with Artificial Intelligence: A strategy for success. European journal of radiology 102:152–156. doi:10.1016/j.ejrad.2018.03.019.

Lindner M, Wenninger S, Fridgen G, Weigold M (2021) Aggregating Energy Flexibility for Demand-Side Management in Manufacturing Companies – A Two-Step Method. Production at the Leading Edge of Technology.

Lins S, Pandl KD, Teigeler H, Thiebes S, Bayer C, Sunyaev A (2021) Artificial Intelligence as a Service. Business & Information Systems Engineering 63(4):441–456. doi:10.1007/s12599-021-00708-w.

Liu Z, Sun Y, Xing C, Liu J, He Y, Zhou Y, Zhang G (2022) Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: Challenges and future perspectives. Energy and AI 10:100195. doi:10.1016/j.egyai.2022.100195.

Loureiro SMC, Guerreiro J, Tussyadiah I (2021) Artificial intelligence in business: State of the art and future research agenda. Journal of Business Research 129:911–926. doi:10.1016/j.jbusres.2020.11.001.

Maedche A, Legner C, Benlian A, Berger B, Gimpel H, Hess T, Hinz O, Morana S, Söllner M (2019) AI-Based Digital Assistants. Business & Information Systems Engineering 61(4):535–544. doi:10.1007/s12599-019-00600-8.

Maglio PP, Lim C-H (2016) Innovation and Big Data in Smart Service Systems. Journal of Innovation Management 4(1):11–21. doi:10.24840/2183-0606_004.001_0003.

Maglio PP, Spohrer J (2013) A service science perspective on business model innovation. Industrial Marketing Management 42(5):665–670. doi:10.1016/j.indmarman.2013.05.007.

Marquardt K (2017) Smart services – characteristics, challenges, opportunities and business models. Proceedings of the International Conference on Business Excellence 11(1):789–801. doi:10.1515/picbe-2017-0084.

Matschoss K, Kahma N (2015) Service interest and cluster membership - Who are the pioneering users in energy efficiency service markets? Nordic Journal of Business 64(2):139–159.

Matschoss K, Kahma N, Heiskanen E (2015) Pioneering customers as change agents for new energy efficiency services—an empirical study in the Finnish electricity markets. Energy Efficiency 8(5):827–843. doi:10.1007/S12053-014-9300-8.

Mehrotra KG, Mohan CK, Huang H (2017) Anomaly Detection Principles and Algorithms. Springer International Publishing, Cham.

Moreno JB, Timms M, Wildberger K (2019) How Artificial Intelligence is accelerating the Energy Transition.

Nickerson RC, Varshney U, Muntermann J (2013) A method for taxonomy development and its application in information systems. European Journal of Information Systems 22(3):336–359. doi:10.1057/ejis.2012.26.

Oberländer AM, Lösser B, Rau D (2019) Taxonomy Research in Information Systems: A Systematic Assessment. In: Proceedings of the 27th European Conference on Information Systems, Stockholm.

Østerlund C, Jarrahi MH, Willis M, Boyd K, Wolf C (2021) Artificial intelligence and the world of work, a co-constitutive relationship. Journal of the Association for Information Science and Technology 72(1):128–135. doi:10.1002/asi.24388.

Paschen J, Wilson M, Ferreira JJ (2020) Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons 63(3):403–414. doi:10.1016/j.bushor.2020.01.003.

Paukstadt U (2019) A Survey of Smart Energy Services for Private Households. Proceedings of the 14th International Conference on Wirtschaftsinformatik.

Paukstadt U, Becker J (2021a) From Energy as a Commodity to Energy as a Service—A Morphological Analysis of Smart Energy Services. Schmalenbach Journal of Business Research 73(2):207–242. doi:10.1007/S41471-021-00111-X.

Paukstadt U, Becker J (2021b) Uncovering the business value of the internet of things in the energy domain – a review of smart energy business models. Electronic Markets 31(1):51–66. doi:10.1007/s12525-019-00381-8.

Paukstadt U, Gollhardt T, Blarr M, Chasin F, Becker J (2019a) A TAXONOMY OF CONSUMER-ORIENTED SMART ENERGY BUSINESS MODELS. Proceedings of the 27th European Conference on Information Systems (ECIS).

Paukstadt U, Strobel G, Eicker S (2019b) UNDERSTANDING SERVICES IN THE ERA OF THE INTERNET OF THINGS: A SMART SERVICE TAXONOMY. Proceedings of the 27th European Conference on Information Systems (ECIS).

Peffers K, Tuunanen T, Gengler CE, Rossi M, Hui W, Virtanen V, Bragge J (2020) Design Science Research Process: A Model for Producing and Presenting Information Systems Research. doi:10.48550/arXiv.2006.02763.

Pourzolfaghar Z, Helfert M (2017) Taxonomy of Smart Elements for Designing Effective Services. AMCIS 2017 Proceedings.

Preidel M, Stark R (2021) SemDaServ: A Systematic Approach for Semantic Data Specification of AI-Based Smart Service Systems. Applied Sciences 11(11):5148. doi:10.3390/app11115148.

Pressmair G, Kapassa E, Casado-Mansilla D, Borges CE, Themistocleous M (2021) Overcoming barriers for the adoption of Local Energy and Flexibility Markets: A user-centric and hybrid model. Journal of Cleaner Production 317:128323. doi:10.1016/j.jclepro.2021.128323.

Pumplun L, Tauchert C, Heidt M (2019) A new organizational chassis for artificial intelligence-exploring organizational readiness factors. In: Proceedings of the 27th European Conference on Information Systems, Stockholm.

Rai A, Constantinides P, Sarker S (2019) Next generation digital platforms : toward human-AI hybrids. MIS Quarterly 43(1):iii–ix.

Raisch S, Krakowski S (2021) Artificial Intelligence and Management: The Automation–Augmentation Paradox. Academy of Management Review 46(1):192–210. doi:10.5465/amr.2018.0072.

Ransbotham S, Khodabandeh S, Kiron D, Candelon F, Chu M, LaFountain B (2020) Expanding AI's Impact With Organizational Learning. MIT Sloan Management Review and Boston Consulting Group.

Rao AS, Verweij G (2017) Sizing the prize: What’s the real value of AI for your business and how can you capitalise?

Ren P, Xiao Y, Chang X, Huang P-Y, Li Z, Gupta BB, Chen X, Wang X (2022) A Survey of Deep Active Learning. ACM Computing Surveys 54(9):1–40. doi:10.1145/3472291.

Rožanec JM, Trajkova E, Dam P, Fortuna B, Mladenić D (2022) Streaming Machine Learning and Online Active Learning for Automated Visual Inspection. IFAC-PapersOnLine 55(2):277–282. doi:10.1016/j.ifacol.2022.04.206.

Ruano A, Hernandez A, Ureña J, Ruano M, Garcia J (2019) NILM Techniques for Intelligent Home Energy Management and Ambient Assisted Living: A Review. Energies 12(11):2203. doi:10.3390/en12112203.

Rusche S, Rockstuhl S, Wenninger S (2021) Quantifizierung unternehmerischer Nachhaltigkeit in der Fertigungsindustrie: Entwicklung eines zielorientierten Nachhaltigkeitsindex. Zeitschrift für Energiewirtschaft 45(4):317–343. doi:10.1007/s12398-021-00312-1.

Rzepka C, Berger B (2018) User Interaction with AI-enabled Systems: A Systematic Review of IS Research. In: Proceedings of the 39th International Conference on Information Systems, San Francisco, CA.

Sarker S, Chatterjee S, Xiao X, Elbanna A (2019) The Sociotechnical Axis of Cohesion for the IS Discipline: Its Historical Legacy and its Continued Relevance. MIS Quarterly 43(3):695–719. doi:10.25300/MISQ/2019/13747.

Scheubel C, Zipperle T, Tzscheutschler P (2017) Modeling of industrial-scale hybrid renewable energy systems (HRES) – The profitability of decentralized supply for industry. Renewable Energy 108:52–63. doi:10.1016/j.renene.2017.02.038.

Seeber I, Bittner E, Briggs RO, Vreede T de, Vreede G-J de, Elkins A, Maier R, Merz AB, Oeste-Reiß S, Randrup N, Schwabe G, Söllner M (2020) Machines as teammates: A research agenda on AI in team collaboration. Information & Management 57(2):103174. doi:10.1016/j.im.2019.103174.

Seow Y, Rahimifard S (2011) A framework for modelling energy consumption within manufacturing systems. CIRP Journal of Manufacturing Science and Technology 4(3):258–264. doi:10.1016/j.cirpj.2011.03.007.

Shin W, Han J, Rhee W (2021) AI-assistance for predictive maintenance of renewable energy systems. Energy 221:119775. doi:10.1016/j.energy.2021.119775.

Sjödin D, Parida V, Palmié M, Wincent J (2021) How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. Journal of Business Research 134:574–587. doi:10.1016/j.jbusres.2021.05.009.

Sonnenberg C, vom Brocke J (2012) Evaluation Patterns for Design Science Research Artefacts. In: Helfert M, Donnellan B (eds) Practical Aspects of Design Science. EDSS

2011. Communications in Computer and Information Science. Springer, Berlin, Heidelberg, pp 71–83.

Spieth P, Schneckenberg D, Ricart JE (2014) Business model innovation – state of the art and future challenges for the field. R&D Management 44(3):237–247. doi:10.1111/radm.12071.

Sturm T, Gerlacha J, Pumplun L, Mesbah N, Peters F, Tauchert C, Nan N, Buxmann P (2021) Coordinating Human and Machine Learning for Effective Organization Learning. MIS Quarterly 45(3):1581–1602. doi:10.25300/MISQ/2021/16543.

TeamLease Digital (2023) iCET - Forces Shaping Future of Technology: Artificial Intelligence.

The Federal Government of Germany (2020) Artificial Intelligence Strategy of the German Federal Government: 2020 Update.

Thiebes S, Lins S, Sunyaev A (2021) Trustworthy artificial intelligence. Electronic Markets 31(2):447–464. doi:10.1007/s12525-020-00441-4.

Töytäri P, Turunen T, Klein M, Eloranta V, Biehl S, Rajala R, Hakanen E (2017) Overcoming Institutional and Capability Barriers to Smart Services. Hawaii International Conference on System Sciences.

Traumer F, Oeste-Reiß S, Leimeister JM (2017) Towards a Future Reallocation of Work between Humans and Machines Taxonomy of Tasks and Interaction Types in the Context of Machine Learning. In: Proceedings of the 38th International Conference on Information Systems, Seoul.

van Leeuwen R, Koole G (2023) Anomaly detection in univariate time series incorporating active learning. Journal of Computational Mathematics and Data Science 6:100072. doi:10.1016/j.jcmds.2022.100072.

Vanden Haute C, Pire T (2020) Maintenance intervals for MP-TP bolted connections – A case study. Results in Engineering 5:100064. doi:10.1016/j.rineng.2019.100064.

Verma S, Singh S, Majumdar A (2021) Multi-label LSTM autoencoder for non-intrusive appliance load monitoring. Electric Power Systems Research 199:107414. doi:10.1016/j.epsr.2021.107414.

Windmark C, Bushlya V, Ståhl J-E (2018) CPR a general Cost Performance Ratio in Manufacturing-A KPI for judgement of different technologies and development scenarios. Procedia CIRP 72:1220–1226. doi:10.1016/j.procir.2018.03.106.

Winter J (2023) Implementing Smart Services in Small- and Medium-Sized Manufacturing Companies: On the Progress of Servitization in the Era of Industry 4.0. Sci 5(3):29. doi:10.3390/sci5030029.

Wolf V, Franke A, Bartelheimer C, Beverungen D (2020) Establishing Smart Service Systems is a Challenge: A Case Study on Pitfalls and Implications. In: Gronau N, Heine M, Poustcchi K, Krasnova H (eds) WI2020 Community Tracks. GITO Verlag, pp 103–119.

World Economic Forum (2015) Industrial Internet of Things: Unleashing the Potential of Connected Products and Services. http://www3.weforum.org/docs/WEFUSA_IndustrialInternet_Report2015.pdf. Accessed 2018-11-27.

Wuenderlich NV, Heinonen K, Ostrom AL, Patricio L, Sousa R, Voss C, Lemmink JG (2015) "Futurizing" smart service: implications for service researchers and managers. Journal of Services Marketing 29(6/7):442–447. doi:10.1108/JSM-01-2015-0040.

Yu Z, Kaplan Z, Yan Q, Zhang N (2021) Security and Privacy in the Emerging Cyber-Physical World: A Survey. IEEE Communications Surveys & Tutorials 23(3):1879–1919. doi:10.1109/COMST.2021.3081450.

Zhao T, Zheng Y, Wu Z (2022) Improving computational efficiency of machine learning modeling of nonlinear processes using sensitivity analysis and active learning. Digital Chemical Engineering 3:100027. doi:10.1016/j.dche.2022.100027.

Zhou X, Feng J, Li Y (2021) Non-intrusive load decomposition based on CNN–LSTM hybrid deep learning model. Energy Reports 7:5762–5771. doi:10.1016/j.egyr.2021.09.001.

V Appendix

1 Index of Research Articles

Research Article #1: Disentangling Human-AI Hybrids: Conceptualizing the Interworking of Humans and AI-Enabled Systems

Fabri, Lukas; Häckel, Björn; Oberländer, Anna Maria; Rieg, Marius; Stohr, Alexander: Disentangling Human-AI Hybrids: Conceptualizing the Interworking of Humans and AI-Enabled Systems. *Business & Information Systems Engineering (2023)*

(VHB-Jourqual 3: Category B | Impact Factor (2023): 5.675)

Research Article #2: How to Select Algorithm for Predictive Maintenance: An Economic Decision Model and Real-world Instantiation

Fabri, Lukas; Häckel, Björn; Oberländer, Anna Maria; Keller, Robert: How to Select Algorithm for Predictive Maintenance: An Economic Decision Model and Real-world Instantiation. *Working Paper in 3rd Revision.* Earlier version published in *Proceedings of the 27th European Conference on Information Systems (ECIS 2019). Stockholm & Uppsala, Sweden.*

Research Article #3: Unraveling the Complexity: A Taxonomy for Characterizing and Structuring Smart Energy Services

Fabri, Lukas; Weißflog, Jan; Wenninger, Simon: Unraveling the Complexity: A Taxonomy for Characterizing and Structuring Smart Energy Services. *Journal of Cleaner Production (2024)*

(VHB-Jourqual 3: Category B | Impact Factor (2024): 9.7)

Research Article #4: Developing a business model framework for industrial data-driven services - a non-intrusive load monitoring case study

Günter, Jennifer; Fabri, Lukas; Kaymakci, Can; Wenninger, Simon: Developing a business model framework for industrial data-driven services - a non-intrusive load monitoring case study. *Working Paper in 2nd Revision.*

Research Article #5: Fostering Non-Intrusive Load Monitoring for Smart Energy Management in Industrial Manufacturing: An Active Machine Learning Approach

Fabri, Lukas; Leuthe, Daniel; Schneider, Lars-Manuel; Wenninger, Simon: Understanding Data Challenges for AI-based services in the energy domain. *Submitted Working Paper.*

I also co-authored the further white papers and Research Articles throughout the doctoral thesis, which are not part of this doctoral thesis. Articles published up to the submission of the doctoral thesis can be found below:

Duda, Sebastian; Fabri, Lukas; Kaymakci, Can; Wenninger, Simon; Sauer, Alexander: **Deriving Digital Energy Platform Archetypes for Manufacturing: A Data-Driven Clustering Approach.** *Proceedings of the 4th Conference on Production Systems and Logistics (CPSL), 2023*

Kaymakci, Can; Bauer, Dennis; Sauer, Alexander; Fabri, Lukas; Wenninger, Simon; Kracker, Florian: **Eine strukturierte Methode zur IT-Systemanalyse für Energieflexibilität in der Industrie**. *Zeitschrift für Energiewirtschaft* (2023)

Amend, Julia; Arnold, Laurin; Fabri, Lukas; Feulner, Simon; Fridgen, Gilbert; Harzer, Linda; Karnebogen, Philip; Köhler, Franziska; Ollig, Philipp; Rieger, Alexander; Schellinger, Benjamin; Schmidbauer-Wolf, G. M.: **Föderale Blockchain Infrastruktur Asyl (FLORA) : Pilotierung und Evaluation des FLORA-Assistenzsystems im Kontext der AnkER-Einrichtung Dresden.** *Fraunhofer Whitepaper* (2022)

Fabri, Lukas; Häckel, Björn; Stahl, Bastian; Beck, Sebastian; Gabele, Maximilian: How Agile Is Your It Department?: **Development and Application of an Framework-Independent Agile Scaling Maturity Model**. *Proceedings of the 30th European Conference on Information Systems (ECIS). - Timișoara, Romania , 2022*

Fabri, Lukas; Meyer-Hollatz, Tim; Wenninger, Simon: **You Never Share Alone : Quantifying Sharing Platforms' Evolution**. *Proceedings of the International Conference of Center for Business & Industrial Marketing (CBIM). - Atlanta, USA , 2022*

Reinkemeyer, Lars; Grindemann, Philipp; Egli, Vanessa; Röglinger, Maximilian; Marcus, Laura; Fabri, Lukas: **Accelerating Business Transformation With Process Mining Centers of Excellence (CoEs).** *Whitepaper* (2022)

Pelger, Philipp; Kaymakci, Can; Wenninger, Simon; Fabri, Lukas; Sauer, Alexander: **Determining the Product-specific Energy Footprint in Manufacturing.** *Wissenschaftliche Gesellschaft für Produktionstechnik - Jahreskongress 2022* .

Fabri, Lukas; Beck, Sebastian; Klos, Tim; Wetzstein, Selina; Kaymakci, Can; Wenninger, Simon: **Potentials and Challenges of Artificial Intelligence in Financial Technologies.** *Proceedings of the 14th Mediterranean Conference on Information Systems (MCIS). - Catanzaro, Italy , 2022*

Urbach, Nils; Häckel, Björn; Hofmann, Peter; Fabri, Lukas; Ifland, Sebastian; Karnebogen, Philip; Krause, Stefanie; Lämmermann, Luis; Protschky, Dominik; Markgraf, Moritz; Willburger, Lukas: **KI-basierte Services intelligent gestalten : Einführung des KI-Service-Canvas.** *Fraunhofer Whitepaper* (2021)

2 Individual Contribution to the Research Articles

This cumulative doctoral thesis comprises five research articles representing the main body of work. All articles were developed in teams with multiple co-authors. This section details the respective research settings and highlights my individual contributions to each article.

Research Article #1: This research article was developed by a team of five co-authors (Lukas Fabri, Björn Häckel, Anna Oberländer, Marius Rieg, and Alexander Stohr). Regarding the development of the manuscript, I co-developed the initial draft of the research article and was engaged in conceptualizing the results and crafting their implications for theory and practice. Additionally, I was involved in further developing and revising the research article and textual elaboration.

Research Article #2: I co-authored this research article with Björn Häckel, Robert Keller, and Anna Oberländer. Nearly all co-authors jointly developed the decision-support model for choosing the economically favorable algorithm for predictive maintenance. I was involved in all stages of developing this research article, from crafting the initial research idea and manuscript to multiple rounds of textual refinement throughout multiple revisions. Further, I was especially responsible for interpreting the data, including several interviews with industry experts, embedding our research in the existing literature, and textual elaboration of the discussion and contribution.

Research Article #3: This research article was developed by three co-authors (Lukas Fabri, Jan Weißflog, Simon Wenninger). As the leading author of this research article, I developed its basic research idea and concept and was responsible for elaborating the research method, model development, evaluation, and crafting the complete manuscript. Additionally, I was in charge of preparing the article’s refinement and preparing it for submission. While, to a large extent, this article reflects my work, all co-authors promoted the advancement of the paper throughout the entire project.

Research Article #4: I co-authored this research article with Jennifer Günter (leading author), Can Kaymakci, and Simon Wenninger. Regarding the development of the manuscript, I co-developed the coding of the literature sample consisting of a structured literature review and elaborated the insights into the textual paper form. Further, I was responsible for refining the interpretation of the results consisting of the developed canvas. Additionally, I was in charge of preparing the article’s refinement and preparing it for submission.

Research Article #5: This research article was developed by four co-authors (Lukas Fabri, Daniel Leuthe, Manuel Schneider, Simon Wenninger). Regarding the development of the manuscript, I was engaged in revising the literature and embedding the results in the current literature. Further, I was part of crafting their implications for theory and practice. Additionally, I was involved in further developing and revising the research article and textual elaboration.

3 Research Article #1

Disentangling Human-AI Hybrids: Conceptualizing the Interworking of Humans and AI-Enabled Systems

Authors: Fabri, L.; Häckel, B.; Oberländer, A.M.; Rieg, M.; Stohr, A.

Published in: *Business & Information Systems Engineering (BISE) (2023)*

Abstract: Artificial intelligence (AI) offers great potential in organizations. The path to achieving this potential will involve human-AI interworking, as has been confirmed by numerous studies. However, it remains to be explored which direction this interworking of human agents and AI-enabled systems ought to take. To date, research still lacks a holistic understanding of the entangled interworking that characterizes human-AI hybrids, so-called because they form when human agents and AI-enabled systems closely collaborate. To enhance such understanding, this paper presents a taxonomy of human-AI hybrids, developed by reviewing the current literature as well as a sample of 101 human-AI hybrids. Leveraging weak sociomateriality as justificatory knowledge, this study provides a deeper understanding of the entanglement between human agents and AI-enabled systems. Furthermore, a cluster analysis is performed to derive archetypes of human-AI hybrids, identifying ideal–typical occurrences of human-AI hybrids in practice. While the taxonomy creates a solid foundation for the understanding and analysis of human-AI hybrids, the archetypes illustrate the range of roles that AI-enabled systems can play in those interworking scenarios.

Keywords: Human-AI hybrids; Human-AI collaboration; Taxonomy; Archetypes; Sociomateriality

4 Research Article #2

How to Select Algorithm for Predictive Maintenance: An Economic Decision Model and Real-world Instantiation

Working Paper in 3rd round of revision

Authors: Fabri, L.; Häckel, B.; Oberländer, A.M.; Keller, R.

Keywords: Algorithm selection, decision model, economic perspective, machine learning, prediction error, predictive maintenance

Extended Abstract[1]:

The increasing availability of large amounts of data and computing power provides opportunities for research and business (Abbasi et al. 2016; Bichler et al. 2017; Eggert and Alberts 2020; Maass et al. 2018). In the industrial context, the increasing connectivity of physical equipment and the corresponding availability of data dramatically increase the potential use of Machine learning in, e.g., maintenance strategies (Agrawal et al. 2018; vom Brocke et al. 2018). As maintenance is one of industrial production's most significant cost drivers (Windmark et al. 2018), applying ML to address maintenance needs is particularly promising. Predictive maintenance (PdM) approaches leverage collected data and ML algorithms to predict upcoming failures and corresponding maintenance needs, preventing breakdowns and reducing maintenance cost (Chen et al. 2019; World Economic Forum 2015).

Reduced maintenance cost resulting from PdM use holds particular value potential for full-service providers (FSPs) business models. An FSP ensures the operational availability of a system and holds responsibility for any maintenance efforts (Huber and Spinler 2012). For the evaluation, comparison, and selection of PdM algorithms, a variety of statistical measures have been considered hitherto. Examples are mean error, root mean squared error, or mean absolute percentage error (e.g., Baptista et al. (2018)). However, a purely statistical approach to algorithm selection may not necessarily lead to the optimal economic outcome, as the two types of prediction errors (alpha error and beta error) are negatively correlated and, thus, cannot be jointly optimized, and are associated with different cost.

In the current literature, much Machine Learning research, particularly in the industrial domain,

[1] At the time of writing, this research article is under review for publication in a scientific journal. Therefore,an extended abstract, taken from the research article, is provided here

uses real-world data and builds and evaluates algorithms for predictions (e.g., maintenance events). However, economic calibration – especially in the industrial domain - has been underrepresented. Thus, existing approaches may not provide sufficient a priori decision support to companies aiming to introduce PdM. However, the different cost implications of the two prediction errors have already been shown in other contexts (e.g., Jiang and Cukic (2009), Kim et al. (2012)). Against this backdrop, we seek to guide PdM algorithm selection from an economic perspective based on the cost implications of alpha errors and beta errors. We argue that the different prediction-based actions and corresponding cost related to the algorithms' error types must be understood, as alpha errors and beta errors do not necessarily lead to the same actions and cost. This is especially relevant for the business model of FSPs since FSPs bear all cost and risks for maintaining operational availability (Hou and Neely 2018) and usually pay a penalty if the agreed-upon level of service availability cannot be met (Huber and Spinler 2012).

Consequently, we developed a decision model for industrial full-service providers, applying an economic perspective to selecting predictive maintenance algorithms. The decision model was instantiated and evaluated in a real-world setting with a European machinery company providing full-service solutions in car wash systems. Building on sensor data from 4.9 million car wash cycles, the instantiation demonstrates the applicability and effectiveness of the decision model with fidelity to a real-world phenomenon. In sum, the decision model provides economic insights into the trade-off between the algorithms' error types and enables users to focus on economic concerns in algorithm selection. Our work contributes to the prescriptive knowledge of algorithm selection and predictive maintenance in line with the consideration of different types of cost.

References

Abbasi A, Sarker S, Chiang R (2016) Big Data Research in Information Systems: Toward an Inclusive Research Agenda. *Journal of the Association for Information Systems* 17(2):I–XXXII. doi:10.17705/1jais.00423.

Agrawal A, Gans J, Goldfarb A (2018) *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Review Press, Boston, Massachusetts.

Baptista M, Sankararaman S, Medeiros IP de, Nascimento C, Prendinger H, Henriques EM (2018) Forecasting fault events for predictive maintenance using data-driven techniques and ARMA modeling. *Computers & Industrial Engineering* 115:41–53. doi:10.1016/j.cie.2017.10.033.

Bichler M, Heinzl A, van der Aalst WMP (2017) Business Analytics and Data Science: Once Again? *Business & Information Systems Engineering* 59(2):77–79. doi:10.1007/s12599-016-0461-1.

Chen C, Liu Y, Sun X, Di Cairano-Gilfedder C, Titmus S (2019) Automobile Maintenance Prediction Using Deep Learning with GIS Data. *Procedia CIRP* 81:447–452. doi:10.1016/j.procir.2019.03.077.

Eggert M, Alberts J (2020) Frontiers of business intelligence and analytics 3.0: a taxonomy-based literature review and research agenda. *Business Research* 13(2):685–739. doi:10.1007/s40685-020-00108-y.

Hou J, Neely A (2018) Investigating risks of outcome-based service contracts from a provider's perspective. *International Journal of Production Research* 56(6):2103–2115. doi:10.1080/00207543.2017.1319089.

Huber S, Spinler S (2012) Pricing of full-service repair contracts. *European Journal of Operational Research* 222(1):113–121. doi:10.1016/j.ejor.2012.04.012.

Jiang Y, Cukic B (2009) Misclassification cost-sensitive fault prediction models. In: Ostrand T (ed) *Proceedings of the 5th International Conference on Predictor Models in Software Engineering - PROMISE '09*. ACM Press, New York, New York, USA, p 1.

Kim J, Choi K, Kim G, Suh Y (2012) Classification cost: An empirical comparison among traditional classifier, Cost-Sensitive Classifier, and MetaCost. *Expert Systems with Applications* 39(4):4013–4019. doi:10.1016/j.eswa.2011.09.071.

Maass W, Parsons J, Purao S, Storey VC, Woo C (2018) Data-Driven Meets Theory-Driven Research in the Era of Big Data: Opportunities and Challenges for Information Systems Research. *Journal of the Association for Information Systems* 19(12):1253–1273. doi:10.17705/1jais.00526.

vom Brocke J, Maaß W, Buxmann P, Maedche A, Leimeister JM, Pecht G (2018) Future Work and Enterprise Systems. *Business & Information Systems Engineering* 60(4):357–366. doi:10.1007/s12599-018-0544-2.

Windmark C, Bushlya V, Ståhl J-E (2018) CPR a general Cost Performance Ratio in Manufacturing-A KPI for judgement of different technologies and development scenarios. *Procedia CIRP* 72:1220–1226. doi:10.1016/j.procir.2018.03.106.

World Economic Forum (2015) *Industrial Internet of Things: Unleashing the Potential of Connected Products and Services*. http://www3.weforum.org/docs/WEFUSA_IndustrialInternet_Report2015.pdf. Accessed 2018-11-27.

5 Research Article #3

Unraveling the Complexity: A Taxonomy for Characterizing and Structuring Smart Energy Services

Authors: Fabri, L.; Weißflog, J.; Wenninger, S.

Published in: *Journal of Cleaner Production (2024)*

Abstract: Achieving climate goals requires restructuring the current energy systems, which, among other things, involves decentralizing energy systems. This entails new challenges, e.g., a high degree of coordination and information exchange. Especially the building sector, being the largest energy consumer, offers great improvement potential to reduce emissions. Smart energy services promise various benefits in overcoming these challenges, e.g., through optimized energy generation, demand control, and more efficient energy control systems. Although smart energy services are crucial to transitioning to a more sustainable, reliable, and intelligent energy (eco)system, research lacks a holistic perspective of their essential characteristics and configuration options due to their novelty and heterogeneity. Nevertheless, this perspective is crucial as service providers, service innovators (e.g., business development and start-ups), and researchers face problems developing and deploying value-adding and sustaining smart energy services. Consequently, this work identifies the essential characteristics of building-related smart energy services by reviewing scientific and practitioner literature. It structures them by developing a taxonomy and organizing them in 15 dimensions and 54 characteristics, along smart energy service structure, value creation, delivery, and energy-related data input. The taxonomy and the derived theoretical and managerial implications support researchers and practitioners in designing and conceptualizing future smart energy service innovations.

Keywords: Data-driven energy management; Smart energy services; Smart services; Taxonomy

6 Research Article #4

Developing a business model framework for industrial data-driven services - a non-intrusive load monitoring case study

Working Paper in 2nd round of revision

Authors: Günter, J.; Fabri, L.; Kaymakci, C.; Wenninger, S.;

Keywords: Nonintrusive load monitoring; Business model; Data-driven services; Smart energy services; Smart manufacturing; Sustainable manufacturing

Extended Abstract[1]:

With the increasing impact of climate change and the tightening of climate policy, industrial companies face the challenges of becoming more sustainable. Nowadays and into the future, with a volatile electricity supply, the economic pressure on the industrial sector will rise (Bauer et al. 2021; Glenk et al. 2021; Paukstadt and Becker 2021). Consequently, the industrial sector sees its competitiveness threatened due to rising CO2 and energy prices (Rusche et al. 2021). Consumption transparency is a prerequisite for energy efficiency and leveraging energy flexibility potentials with energy management systems (Lindner et al. 2021; Seow and Rahimifard 2011). For instance, transparency allows monitoring the overall condition of appliances and enables identifying inefficient operating modes or imminent failures to take predictive measures to reduce efficiency losses and downtime.

Consequently, with advances in digitization, research has brought new approaches like smart energy services to uncover the causes of energy consumption. Smart energy services go beyond core functions of energy consumption billing as they enable, for example, the optimization of energy consumption. Hence, smart energy services like NILM are gaining importance as they help to improve energy efficiency and flexibility, which are becoming increasingly significant assets to counter rising economic pressure (Bauer et al. 2021; Glenk et al. 2021; Paukstadt and Becker 2021). However, research on NILM in industrial applications almost exclusively investigates technical aspects.

Current literature in the industrial sector studies almost exclusively technical aspects, such as optimizing different algorithms to achieve higher accuracy (e.g., Li et al. (2021)). Furthermore,

[1] At the time of writing, this research article is under review for publication in a scientific journal. Therefore,an extended abstract, taken from the research article, is provided here

the scientific literature offers little evidence to support the adoption of smart energy services such as NILM, even though they offer an economic advantage over expensive sub-meters (Armel et al. 2013; Bucci et al. 2021; Hosseini et al. 2017; Yi et al. 2019). Consequently, a business model perspective is hardly considered. However, to leverage the business potential of smart energy services in a more digital manufacturing environment, a business model framework that enables structuring and developing a business model for NILM as a representative smart energy service for industrial applications is needed.

To provide a complete picture of a smart, data-based energy monitoring service, we derived 59 hypotheses, which should provide a suitable basis for conceptualizing a service- and technology-oriented business model. First, we examine the status quo in the existing literature regarding smart services, service-oriented business models, and smart energy services like NILM to derive hypotheses for building the SCSC. Then, we empirically evaluate these hypotheses and further refine them with the help of expert interviews. We argue that by providing a methodically sound and practical SCSC, we contribute to literature and practice by complementing the ongoing, mainly technological-focused research activities. We thereby help to accelerate the introduction of smart energy services like NILM to the industrial sector.

References

Armel KC, Gupta A, Shrimali G, Albert A (2013) Is disaggregation the holy grail of energy efficiency? Energy Policy, vol. 52:213–234.

Bauer D, Hieronymus A, Kaymakci C, Köberlein J, Schimmelpfennig J, Wenninger S, Zeiser R (2021) Wie IT die Energieflexibilitätsvermarktung von Industrieunternehmen ermöglicht und die Energiewende unterstützt. HMD Praxis der Wirtschaftsinformatik 58(1):102–115. doi:10.1365/s40702-020-00679-8.

Bucci G, Ciancetta F, Fiorucci E, Mari S, Fioravanti A (2021) State of art overview of Non-Intrusive Load Monitoring applications in smart grids. Measurement: Sensors 18:100145. doi:10.1016/j.measen.2021.100145.

Glenk G, Meier R, Reichelstein S (2021) Cost Dynamics of Clean Energy Technologies. Schmalenbach Journal of Business Research:1–28. doi:10.1007/s41471-021-00114-8.

Hosseini SS, Agbossou K, Kelouwani S, Cardenas A (2017) Non-intrusive load monitoring through home energy management systems: A comprehensive review. Renewable and Sustainable Energy Reviews 79:1266–1274. doi:10.1016/j.rser.2017.05.096.

Li Y, Wang H, Yang J, Wang K, Qi G (2021) A non-intrusive load monitoring algorithm based on multiple features and decision fusion. Energy Reports 7:1555–1562. doi:10.1016/j.egyr.2021.09.087.

Lindner M, Wenninger S, Fridgen G, Weigold M (2021) Aggregating Energy Flexibility for Demand-Side Management in Manufacturing Companies – A Two-Step Method. Production at the Leading Edge of Technology.

Paukstadt U, Becker J (2021) Uncovering the business value of the internet of things in the energy domain – a review of smart energy business models. Electronic Markets 31(1):51–66. doi:10.1007/s12525-019-00381-8.

Rusche S, Rockstuhl S, Wenninger S (2021) Quantifizierung unternehmerischer Nachhaltigkeit in der Fertigungsindustrie: Entwicklung eines zielorientierten Nachhaltigkeitsindex. Zeitschrift für Energiewirtschaft 45(4):317–343. doi:10.1007/s12398-021-00312-1.

Seow Y, Rahimifard S (2011) A framework for modelling energy consumption within manufacturing systems. CIRP Journal of Manufacturing Science and Technology 4(3):258–264. doi:10.1016/j.cirpj.2011.03.007.

Yi S, Yin X, Diao Y, Wang B, Wu P (2019) A New Event-detection Method Based on Composite Windows in NILM for Industrial Settings. IEEE Sustainable Power and Energy Conference (iSPEC):2768–2771.

7 Research Article #5

Fostering Non-Intrusive Load Monitoring for Smart Energy Management in Industrial Manufacturing: An Active Machine Learning Approach

Working Paper

Authors: Fabri, L.; Leuthe, D.; Schneider L.-M.; Wenninger, S.

Keywords: Active Learning; Energy efficiency; Machine Learning; Non-Intrusive Load Monitoring; Smart Energy Management

Extended Abstract[1]:

Companies introduce smart energy management to enforce energy reduction (Zhang et al. 2022; Ali et al. 2021). Non-Intrusive Load Monitoring (NILM) is an emerging approach to enable more sophisticated smart energy management (Cui et al. 2022; Liu et al. 2022; Angelis et al. 2022). NILM estimates the power consumption of individual applications from aggregated power measurements (Gopinath et al. 2020; Hart 1992). In contrast to intrusive load monitoring, NILM equalizes the implementation of expensive submetering while providing valuable information for energy-saving decision-making (Cui et al. 2022). Use cases of NILM include energy monitoring, demand side management, peak shaving, job scheduling and anomaly, and fault detection for saving energy (Barth et al. 2018; Bergman et al. 2011; Gopinath et al. 2020). For example, early detection of those faults or anomalies with the help of NILM avoids economic, energy, and environmental losses due to, e.g., maintenance cost reduction, machine fault reduction, increased spare part life, or the identification of inefficient applications (Gopinath et al. 2020).

However, besides the lack of feasible industrial time series data, the key challenge of NILM in industrial manufacturing is the scarcity of labeled data, leading to costly and time-consuming workflows. Current NILM research focuses on technical and data science dimensions, including mathematical optimization and supervised and unsupervised machine learning algorithms (Cui et al. 2022). However, although NILM has existed for decades, it has not been widely adopted in industrial manufacturing (Holmegaard and Baun Kjaergaard 2016; Cui et al. 2022; Gopinath et al. 2020). The reasons are NILM's complexity and the lack of industrial data labels for

[1] At the time of writing, this research article is under review for publication in a scientific journal. Therefore,an extended abstract, taken from the research article, is provided here

promising supervised algorithms (Feng and Tian 2021). Nevertheless, labeling new data in an industrial environment requires domain-specific knowledge, is time-consuming and expensive to obtain - and is often unattractive in practice (Feng and Tian 2021; Yu et al. 2021). To reduce labeling efforts, research introduced the concept of active learning (Settles 2010; Guo et al. 2020), which is applied in various disciplines (Das et al. 2016; Ren et al. 2022; Angelis et al. 2022; Kumar and Gupta 2020). However, active learning has gathered little attention in the context of NILM (Jin 2016).

We develop an active learning model using the HIPE data set based on a real-world production plant (Bischof et al. 2018). We implement our model to validate the underlying concept of reducing the labeling effort. Our methodology is based on the Cross-Industry Standard Process for Data Mining (CRISP-DM). The proposed model does not replace existing NILM techniques. Instead, it complements its techniques by significantly reducing data labeling and user effort while maintaining appropriate disaggregation accuracies. Hence, we reduce the concerns about the cost of NILM and make them more applicable for reducing energy consumption.

This work contributes to research and practice in three ways. First, we combine the two research streams on NILM for industrial manufacturing (Kalinke et al. 2021; Gopinath et al. 2020) and the research on active learning (Das et al. 2016; Finder et al. 2022). Second, we develop an active learning model, define the best-performing architecture depending on the disaggregation algorithms to separate individual applications' energy consumption, and compare three query strategies to efficiently select a subset of the training data. Third, the resulting active learning model fosters the introduction of a cost-effective NILM system that enables practitioners to save energy through smarter energy management and contribute to cleaner production.

References:

Ali M, Prakash K, Hossain MA, Pota HR (2021) Intelligent energy management: Evolving developments, current challenges, and research directions for sustainable future. Journal of Cleaner Production 314:127904. doi:10.1016/j.jclepro.2021.127904.

Angelis G-F, Timplalexis C, Krinidis S, Ioannidis D, Tzovaras D (2022) NILM applications: Literature review of learning approaches, recent developments and challenges. Energy and Buildings 261:111951. doi:10.1016/j.enbuild.2022.111951.

Barth L, Hagenmeyer V, Ludwig N, Wagner D (2018) How much demand side flexibility do we need? In: Proceedings of the Ninth International Conference on Future Energy Systems. ACM, New York, NY, USA, pp 43–62.

Bergman D, Jin D, Juen J, Tanaka N, Gunter C, Wright A (2011) Nonintrusive Load-Shed Verification. IEEE Pervasive Computing 10(1):49–57. doi:10.1109/MPRV.2010.71.

Bischof S, Trittenbach H, Vollmer M, Werle D, Blank T, Böhm K (2018) HIPE. In: Proceedings of the Ninth International Conference on Future Energy Systems. ACM, New York, NY, USA, pp 599–603.

Cui J, Jin Y, Yu R, Okoye MO, Li Y, Yang J, Wang S (2022) A robust approach for the decomposition of high-energy-consuming industrial loads with deep learning. Journal of cleaner production 349:131208. doi:10.1016/j.jclepro.2022.131208.

Das S, Wong W-K, Dietterich T, Fern A, Emmott A (2016) Incorporating Expert Feedback into Active Anomaly Discovery. In: 2016 IEEE 16th International Conference on Data Mining (ICDM). IEEE, pp 853–858.

Feng C, Tian P (2021) Time Series Anomaly Detection for Cyber-physical Systems via Neural System Identification and Bayesian Filtering. In: Zhu F (ed) Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining. Association for Computing Machinery, New York,NY,United States, pp 2858–2867.

Finder I, Sheetrit E, Nissim N (2022) A time-interval-based active learning framework for enhanced PE malware acquisition and detection. Computers & Security 121:102838. doi:10.1016/j.cose.2022.102838.

Gopinath R, Kumar M, Prakash Chandra Joshua C, Srinivas K (2020) Energy management using non-intrusive load monitoring techniques – State-of-the-art and future research directions. Sustainable Cities and Society 62:102411. doi:10.1016/j.scs.2020.102411.

Guo L, Wang S, Chen H, Shi Q (2020) A Load Identification Method Based on Active Deep Learning and Discrete Wavelet Transform. IEEE Access 8:113932–113942. doi:10.1109/ACCESS.2020.3003778.

Hart GW (1992) Nonintrusive appliance load monitoring. Proceedings of the IEEE 80(12):1870–1891. doi:10.1109/5.192069.

Holmegaard E, Baun Kjaergaard M (2016) NILM in an Industrial Setting: A Load Characterization and Algorithm Evaluation. In: 2016 IEEE International Conference on Smart Computing (SMARTCOMP). IEEE, pp 1–8.

Jin X (2016) Active Learning Framework for Non-Intrusive Load Monitoring: Preprint.

Kalinke F, Bielski P, Singh S, Fouché E, Böhm K (2021) An Evaluation of NILM Approaches on Industrial Energy-Consumption Data. In: Proceedings of the Twelfth ACM International Conference on Future Energy Systems. ACM, New York, NY, USA, pp 239–243.

Kumar P, Gupta A (2020) Active Learning Query Strategies for Classification, Regression, and Clustering: A Survey. Journal of Computer Science and Technology 35(4):913–945. doi:10.1007/s11390-020-9487-4.

Liu Y, Ma J, Xing X, Liu X, Wang W (2022) A home energy management system incorporating data-driven uncertainty-aware user preference. Applied Energy 326:119911. doi:10.1016/j.apenergy.2022.119911.

Ren P, Xiao Y, Chang X, Huang P-Y, Li Z, Gupta BB, Chen X, Wang X (2022) A Survey of Deep Active Learning. ACM Computing Surveys 54(9):1–40. doi:10.1145/3472291.

Settles B (2010) Active Learning Literature Survey. University of Wisconsin, Madison 52. https://minds.wisconsin.edu/handle/1793/60660.

Yu Z, Kaplan Z, Yan Q, Zhang N (2021) Security and Privacy in the Emerging Cyber-Physical World: A Survey. IEEE Communications Surveys & Tutorials 23(3):1879–1919. doi:10.1109/COMST.2021.3081450.

Zhang J, Lyu Y, Li Y, Geng Y (2022) Digital economy: An innovation driving factor for low-carbon development. Environmental Impact Assessment Review 96:106821. doi:10.1016/j.eiar.2022.106821.