From Analysis to Value:
Internet of Things Solutions in Industry, Cities, and Healthcare

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„Die Maschine sagt, das Problem sei nicht, es zu erklären. Das Problem sei, dass wir die Erklärung nicht verstünden.“

(Frank Schätzing)

Ich bedanke mich bei allen, die mich auf dieser Reise begleitet haben.

Abstract

The Internet of Things (IoT) stands out as one of the most revolutionary technologies in today's market, seamlessly merging physical objects into an increasingly connected society. By equipping these physical objects with sensors and actuators, and enabling communication via a network or the Internet, the IoT has spurred exponential growth and has unlocked vast economic opportunities. It has led to separate everyday objects becoming part of a digitally connected world, providing a wide range of tremendous opportunities. The diversity of application fields of the IoT ranges from voice assistants for smart homes, to traffic monitoring in smart cities, to connected machinery in industry.

The IoT is expected to surpass 30 billion devices by 2030, indicating its significant potentials. IoT solutions act as a bridge between suppliers and customers, providing benefits, such as direct product uses for users and backstage analytics for providers. Despite consumers' adoption of IoT, its industrial use lags owing to barriers such as business models and value assessment challenges. While technical aspects have dominated the IoT research, the business perspective requires more attention. This cumulative doctoral thesis sheds light on the development process of IoT solutions and presents six research articles covering three development phases: 1) *analysis and ideation*, 2) *conceptualization and implementation*, and 3) *value assessment and business development*.

Articles #1 and #2 are associated with the *analysis and ideation* phase, each focusing on structuring specific IoT subfields and presenting related taxonomies. Article #1 analyzes the smart city solutions field and presents a taxonomy and corresponding clusters to provide descriptive knowledge on smart cities, laying the foundation for future research in this field. A complementary article, article #2, develops a taxonomy for industrial IoT startups. Both develop taxonomies structure an IoT subfield and offer the possibility to create new IoT solutions as they provide, among others, an impression of what solutions possibilities already exist, what the distribution looks like, and which gaps exist. These two articles also show the possibilities of cooperating with other companies, such as startups, and entering into partnerships.

In the *conceptualization and implementation* phase, this doctoral thesis presents articles #3 and #4, which address developing software architectures as a key element of IoT solutions. Both follow the design science research (DSR) process, which is particularly suitable for the development of artifacts, including software architectures. Article #3 extends the current knowledge and adds design and diagnosis insights regarding descriptive and prescriptive knowledge for smartphone-enabled predictive maintenance (PdM). It introduces a lightweight and affordable PdM solution to lever the low investment costs associated with retail smartphones, which are already ubiquitous. In article #4, this research approach is applied to IoT solutions in healthcare. A wearable IoT system for continual bladder level monitoring in cooperation with the startup inContAlert is developed as a primary artifact. Both articles demonstrate the added value for that sector by developing a

prototype in combination with further evaluation steps and demonstrating contributions for practical application.

Articles #5 and #6 contribute to the *value assessment and business development* phase. As noted, the current market for IoT solutions in industrial environments is falling short of expectations. Both articles examine the question how IoT solutions' value can be systematically assessed. Article #5 presents a framework for assessing IoT solutions' value, considering both indirect and direct value categories and an archetypal business-to-business-to-consumer (B2B2C) value chain. Article #6 extends article #5 by developing a method that provides practitioners with additional step-by-step guidance.

The six articles in this cumulative doctoral thesis provide overall support and guidance for developing IoT solutions throughout the development process. The thesis contributes to the theoretical groundwork in multiple ways. First, it provides a foundation by structuring IoT subfields, allowing researchers to build on this in future to develop theories for explanation. Second, it presents two software architectures, tested and evaluated in close collaboration with five different industrial companies and a software developer, contributing to the DSR knowledge. Third, this thesis presents a framework and a corresponding method for assessing IoT solutions' value. It extends the theoretical knowledge on assessing IoT solutions' value and lays the foundation for their effective monetization and commercialization. This thesis aims to thoroughly and profoundly support and accelerate the dissemination and expansion of the IoT.

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I. Introduction[1]

The Internet of Things (IoT) is one of the most disruptive technologies in the market since it integrates physical objects into a networked society (Oberländer et al., 2018; Püschel et al., 2020). Equipping things with sensors and actuators has been associated with exponential growth and enormous economic potential. The IoT involves physical objects equipped with sensors, actuators, and computation logic, which are able to communicate via a network or the Internet (Oberländer et al., 2018; Porter & Heppelmann, 2014; Yoo et al., 2012). It has led to separate everyday objects becoming part of a digitally connected world, providing a wide range of tremendous opportunities, such as the designing and delivery of IoT solutions (Beverungen et al., 2019; Poeppelbuss & Durst, 2019; Wortmann & Flüchter, 2015).

Kevin Ashton first proposed the IoT concept in 1999, referring to it as uniquely identifiable, interoperable, connected objects with radio frequency identification technology (Li et al., 2015). Later, in 2005, the International Telecommunication Union published the first report on the subject, framing IoT as *"a new dimension that has been added to the world of information and communication technologies (ICTs): from any time, any place connectivity for anyone, we will now have connectivity for anything. Connections will multiply and create an entirely new dynamic network of networks – an Internet of Things"* (International Telecommunication Union, 2005, p. 2). Later, Atzori et al. (2010) defined IoT from a technical perspective as a worldwide network of interconnected objects that are uniquely addressable based on standard communication protocol items. Drawing on no less than 16 specific definitions, Oberländer et al. (2018) broadly defined the IoT as *"the connectivity of physical objects equipped with sensors and actuators to the Internet via data communication technology"* (p. 488), the definition used as a foundation for this doctoral thesis. Based on this, an IoT solution combines physical products with digital services, where value creation shifts to the latter and spans multiple stakeholders for whom direct and indirect benefits are generated (Del Giudice, 2016; Huber et al., 2019; Kasilingam & Krishna, 2022; Sheth, 2016).

Following Fleisch et al. (2014), an IoT solution has five layers: a physical thing, sensors/actuators, connectivity, analytics, and digital services. The physical thing refers to the object, while sensors/actuators are additions to the physical object, such as motion or light sensors, and the connectivity layer allows for communication with either a local network or the Internet. The data analytics layer analyzes large amounts of data properly and combines the collected data with information from various other sources. The digital services layer uses the output of the previous layers to offer it to customers in the form of services. Offering external customers an integration of a physical product and a digital service is referred to as an IoT solution (Bauk et al., 2018;

[1] This section partly comprises content from the thesis' research articles. To improve the readability of the text, I have omitted the standard labeling of these citations.

Fleisch et al., 2014; Weinberger et al., 2016). IoT solutions open new opportunities to collect data and offer new service types, both on the consumer side and in industry contexts (Püschel et al., 2020). In the business-to-consumer (B2C) market, for instance, *consumer IoT* use cases range from smart fridges and car-sharing to intelligent thermostats (Püschel et al., 2020). Here, the IoT is already playing a key role in acquiring more consumer information and data (Yan et al., 2020). In the business-to-business (B2B) market, the IoT can be divided into *commercial IoT* and *industrial IoT* (Munirathinam, 2020). While commercial IoT covers use cases in the service sector, such as healthcare and financial services, industrial IoT (IIoT) – or Industry 4.0, as it is known in German-speaking parts of the world (Geißler et al., 2019; Matthiae & Richter, 2018) – spans a broad range of connected industrial devices and cyber-physical production systems (Geißler et al., 2019; Ransbotham et al., 2016). The number of IoT devices is expected to exceed the magic mark of 30 billion by 2030, highlighting the technology's potential (Statista, 2023).

Following Beverungen et al. (2019), IoT forms a connecting link between suppliers and customers and offers advantages for both sides. On the one hand, users benefit from the direct use of a product by creating and capturing value-in-use via monitoring, optimization, or remote control. On the other hand, providers benefit from backstage analytics, such as remote monitoring and diagnostics, data aggregation, data analytics, or decision-making (Beverungen et al., 2017; G. Gimpel, 2020). This dual value potential offers new opportunities across the entire products and services portfolio. For instance, Kaeser offers *Air as a Service* as an additional business model for selling air compressors (Kaeser, 2022). This business model is only possible because Kaesar's compressors are monitored with sensors and connectors, so that equipment can be serviced and consumption can be measured remotely.

In sum, the IoT is creating product and service types and, thus, value opportunities for customers and suppliers (Almquist et al., 2016). While the IoT has consciously or unconsciously found its way almost everywhere in the consumer sector, its spread in the industrial environment is lagging behind expectations despite the industry's increasing investments in IoT (McKinsey & Company, 2018, 2021; Microsoft et al., 2022; Odusote et al., 2016). Bilgeri and Wortmann (2017) explained this discrepancy with 16 barriers to IoT business model innovation, including commercialization and the associated need for the value assessment of IoT solutions. Similarly, in their review, Nicolescu et al. (2018) concluded that the business perspective on IoT lags behind. This doctoral thesis combines the technical and business perspectives and looks at the entire development process of IoT solutions, from analysis to implementation to business development. Figure 1 – inspired by Matzner et al. (2019) and Jussen et al. (2019) – shows a simplified IoT solutions development process, around which the six research contributions are arranged. As we all navigate these development cycles, it becomes evident that bridging the gap between technical intricacies and business imperatives is crucial for unleashing IoT's full potential and ensuring its pervasive integration across diverse sectors.

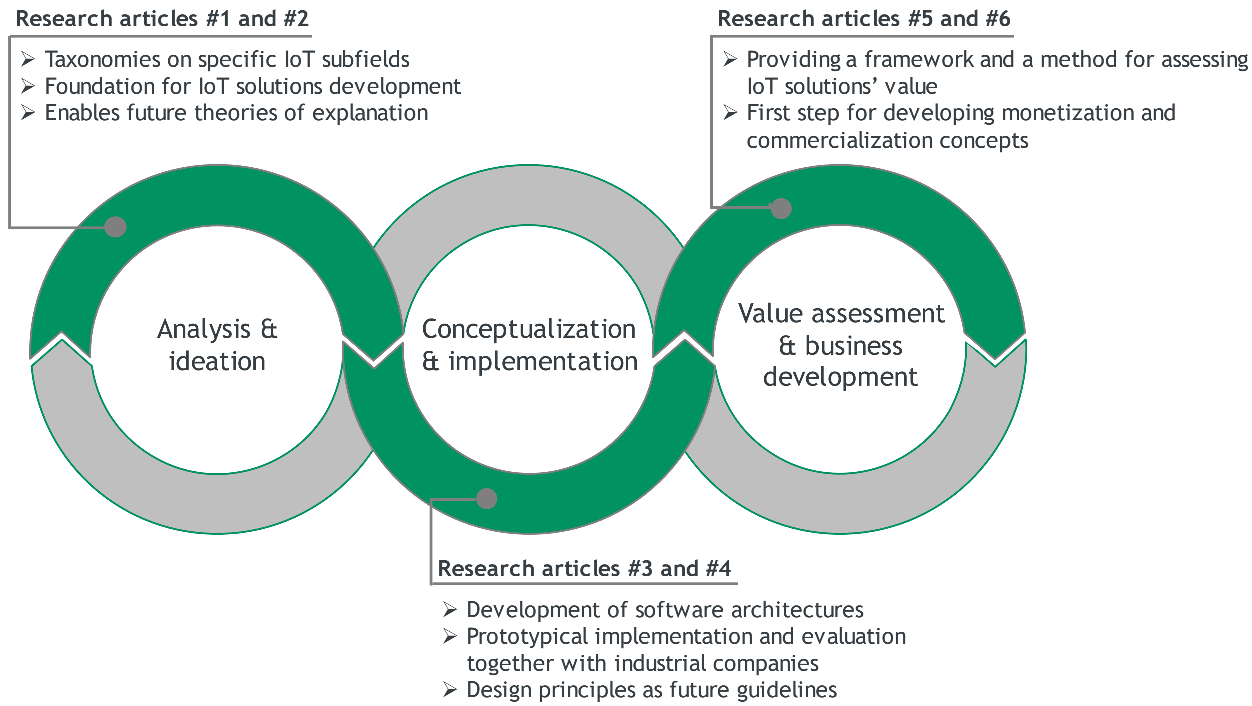

Figure 1: Overview over the Six Research Articles for this Cumulative Doctoral Thesis

Further, this thesis's structure was designed around three phases, which serve as organizing principles for Section II: 1) *analysis and ideation*, 2) *conceptualization and implementation*, and 3) *value assessment and business development*. Phase 1 focuses on analyzing existing IoT solutions as well as finding the 'right' idea to pursue. Phase 2 further extends an idea by developing a concept and implementing IoT solutions. Phase 3 deals with the business perspective on IoT solutions by grasping the value created through the solutions for every stakeholder and developing a business case. As part of the *analysis and ideation* phase, this thesis contributes two taxonomies. First, it provides a taxonomy and corresponding clusters that structure smart city solutions; second, it introduces a taxonomy focusing on IIoT startups (Section II.1, which incorporates articles #1 and #2). Second, the thesis delves into *conceptualization and implementation*, offering two articles on the software architecture development and the prototyping of IoT solutions. Article #3 introduces a software architecture for smartphone-enabled predictive maintenance (PdM) as the primary artifact, while article #4 presents a software architecture derived from the consumer healthcare domain (Section II.2, which encompasses articles #3 and #4). Third, in the *value assessment and business development* phase, this thesis concentrates on the business perspective of developing IoT solutions. Thus, article #5 presents a framework for structuring the value assessment of IoT solutions along an archetypal value chain, while article #6 extends it into a prescriptive method for assessing IoT solutions' value (Section II.3, which incorporates articles #5 and #6).

Besides the range of content, the six articles that feed this cumulative doctoral thesis also show a diverse portfolio of different applied and combined research methods. Articles #1 and #2 follow Nickerson et al.'s (2013) taxonomy development process, combined with a Q-sort evaluation (Nahm et al., 2002). Article #1 supplements the taxonomy development with a quantitative clustering approach (Field, 2013; Hair et al., 2010) using Ward's Hierarchical Agglomerative Algorithm (Ward, 1963). Articles #3 to #6 follow the information systems (IS) community's widespread design science research (DSR) approach (Gregor & Hevner, 2013; Peffers et al., 2007) as fundamental guidelines for developing IS artifacts. Thus, articles #3 and #4 develop software architectures as main artifacts, following Galster and Avgeriou's (2011) construction framework. The evaluation follows: in the first article, Sonnenberg and vom Brocke's (2012) evaluation framework; in the second article, the framework for evaluation in design science research (FEDS) (Venable et al., 2016). Article #5 develops a framework for assessing IoT solutions' value and uses a structured literature review to establish an informed overview over the literature (vom Brocke et al., 2015; Webster & Watson, 2002). Article #6 concludes by developing a method by adapting the DSR process to method development using Situational Method Engineering (Brinkkemper, 1996; Henderson-Sellers et al., 2014).

The thesis structure continues in Section III with a comprehensive summary of the articles, followed by an exposition of the thesis' overall contributions and a glimpse into potential avenues for future research. Section IV contains all references cited throughout this thesis, while Section V (Appendix) includes supplementary information on all the research articles.

II. Overview over and the Contexts of the Six Research Articles[2]

1 Analysis and Ideation

When developing IoT solutions, the first steps are analyzing the market, the competition, and/or the internal company offerings, followed by an ideation of possible solutions. While ideation is not the focus of this thesis, this thesis concentrates on the analysis, i.e., structuring subfields of IoT. For ideation, there is reference to other contributions that have focused on different steps in ideation and have developed frameworks, tools, or methods (Beverungen et al., 2018; Ebel et al., 2022; Exner et al., 2019; Poeppelbuss & Durst, 2019).

When analyzing existing IoT solutions, taxonomies help provide structure in a differentiated field. Taxonomies are classification approaches that consist of dimensions and related characteristics that help to understand, describe, analyze, and classify objects of interest (Miller & Roth, 1994; Nickerson et al., 2013). They can be found in the IoT environment in various subject areas. Püschel et al. (2020), who developed a taxonomy for IoT applications – smart things – in the B2C sector, found that smart things can be divided into archetypes according to *thing-centric* and *service-centric*, as well as their smartness levels. Another taxonomy focuses not only on a single smart thing but also on complementing and expanding the interactions in a value chain, i.e., *business-to-thing* and *customer-to-thing* interactions (Oberländer et al., 2018). To better understand the diverse IoT solutions field, articles #1 and #2 examine subfields in the IoT, each developing a specific taxonomy.

Article #1 analyzes the smart city solutions field, which is very exciting, as demographic developments are predicted to lead to immense growth in cities (UN, 2018). Projections indicate that, owing to urbanization and the global population surge, an estimated 2.5 billion individuals will likely inhabit urban areas by 2050. Asia and Africa are anticipated to strongly contribute to this growth, accounting for nearly 90% of this overall projected increase (UN, 2018). In addressing the challenges posed by expanding urban areas, smart city solutions have a key role. These innovative, digitally empowered approaches offer practical solutions for issues such as traffic monitoring and waste management, exemplified by technologies such as smart bins, which seek to reduce our dependence on waste collection personnel. Smart city solutions *"are technology-based applications that offer a way to reach a smart city goal (i.e., economic, environmental, or social sustainability) to foster the quality of city life"* (Jonas et al., 2023, p. 4).

Studies have delved into various dimensions of smart city solutions, examining both technical and nontechnical aspects, as well as specific subfields in the smart city domain. For instance, Ahmed et al. (2016), Muhammad et al. (2021), and Nagel and Kranz (2020) have concentrated on technical intricacies, developing taxonomies and exploring communication enablers, network types, wireless standards, objectives, and characteristics of

[2] This section partly comprises content from the thesis' research articles. To improve the readability of the text, I have omitted the standard labeling of these citations.

smart environment solutions. In contrast, Vasudavan and Balakrishnan (2019) focused on nontechnical aspects, identifying core factors that define a smart city, such as application areas and the resulting benefits. Further, some studies have narrowed their focus to individual manifestations in the smart city realm. Benevolo et al. (2016) explored mobility aspects, Christmann et al. (2022) delved into urban agriculture, and Rana (2011) contributed to the understanding of urban sustainability. Each of these research endeavors has contributed to a comprehensive understanding of smart city solutions by dissecting specific components or subfields, enriching the collective knowledge base in this rapidly evolving domain. Article #1 used preliminary work to gain a holistic perspective on smart city solutions to provide future researchers with a foundation to explain the smart city phenomenon and to develop predictions on how smart cities will evolve. It also provides practitioners with a foundation to reveal new design opportunities and enable the discovery of as-yet-unknown dependencies, allowing urban planning professionals to take informed implementation decisions on smart city solutions.

The developed taxonomy (Table 1) of smart city solutions has 10 dimensions, each with two to nine characteristics. These dimensions and their associated characteristics are organized into three layers, comprehensively structuring the taxonomy: *solution context*, *technology*, and *value*. The taxonomy development process follows Nickerson et al. (2013), with adaptations from Kundisch et al. (2022) for integrated evaluation. The process also involves four iterations, starting with a conceptual-to-empirical phase, where existing taxonomies from IoT-related fields and the literature on smart cities are integrated. Three empirical-to-conceptual iterations are then conducted, drawing on data from 106 smart city solutions retrieved from the Crunchbase database.

Table 1: Multilayer Taxonomy of Smart City Solutions

	Dimension	Characteristics								
Solution context	Focused smartification area	Building	Commerce	Community	Environment	Governance	Healthcare	Mobility		E
	Solution owner	Citizen	Business	Government						NE
	Solution end-user	Citizen	Business	Government						NE
Technology	Technology application	AI	Mobile app	BC	Camera	Cloud	IoT	PV	WT	NE
	Data stream	Existing data	New data							NE
	Analytics	None	Fundamental	Extensive						E
Value	Main sustainability value	Economic	Environmental	Social						E
	Value proposition	Thing-centric	Service-centric	Platform-centric						E
	Value creation	Instantaneous	Delayed							E
	Dependency	Dependent	Independent							E

E = exclusive dimension (one characteristic at a time); NE = non-exclusive dimension (potentially multiple characteristics observable at a time);
AI = artificial intelligence; BC = blockchain; PV = photovoltaic panel; WT = wind turbine.

The intricate layers of smart city solutions unfold progressively, each contributing insights into the smart cities' multifacetedness. The *solution context* layer describes the smartification area at hand and offers a nuanced understanding of where and how smart technologies are applied. This dimension identifies the target areas, such as governance or healthcare, and provides a lens through which each domain's specific challenges and opportunities can be assessed. The solution owner and its end-users supplement this dimension. The former answers who, from a legal perspective, is the owner of a smart city solution (Demsetz, 1974; McCarty, 2002), while the latter answers who a smart city solution's end-users are. In the second layer, *technology*, the dimensions of technology application, data stream, and analytics unveil the technological intricacies that power smart city initiatives. In this context, the roles of artificial intelligence (AI), mobile applications, and the IoT are acknowledged in shaping the digital landscape of urban environments. The distinction between existing and new data sources underscores the evolving nature of the information that fuels these solutions, while analytics classifications shed light on data-driven insights' depth and sophistication (Püschel et al., 2020). The third layer, *value*, highlights the economic, environmental, and social dimensions that shape a smart city's success (Lehtonen, 2004; Toli & Murtagh, 2020). Considering value propositions as thing-centric, service-centric, or platform-centric unveils the diverse ways in which these solutions deliver impact (Püschel et al., 2020). Understanding the value creation speed (i.e., whether instantaneous or delayed) becomes pivotal in gauging smart city interventions' real-time applicability and efficiency. Further, the dependency dimension emphasizes these solutions' interconnectedness, exploring how some may rely on external inputs, while others operate independently. In sum, this taxonomy not only allows categorizations of smart city solutions but also fosters a holistic understanding of smart city solutions.

Based on the developed taxonomy and the 106 classified smart city solutions, a hierarchical cluster analysis is conducted by applying Ward's Hierarchical Agglomerative Algorithm to cluster the surveyed smart city solutions. This algorithm is selected based on the uncertainty regarding the number of clusters required prior to the analysis (Ferreira & Hitchcock, 2009; Ward, 1963). The chosen algorithm agglomeratively groups objects based on their similarity (Everitt et al., 2011; Ferreira & Hitchcock, 2009; Ward, 1963). Three clusters are identified: *environmentally focused IoT*, *mobility-focused data analytics*, and *citizen-focused everyday mobile apps* (Table 2). Thus, smart city solutions from the first cluster can be described as solutions that focus on improving the environment through IoT technologies and are both operated and used by businesses and the government. Solutions from the second cluster are solutions that address mobility-related problems using a data-driven approach. Finally, solutions in the third cluster make citizens' lives easier by providing mobile apps for diverse application areas.

Table 2: Smart City Solution Clusters

	Cluster	Environmentally focused IoT	Mobility-focused data analytics	Citizen-focused everyday mobile apps
Solution context	Focused smartification area	Environment	Mobility	Commerce, community, mobility
	Solution owner	Business, government	Business, government	Business
	Solution end-users	Business, government	Business, government	Citizens
Technology	Technology application	IoT	AI, IoT	Mobile app
	Data stream	New	New	Existing, new
	Analytics	Fundamental	Extensive	Fundamental
Value	Main sustainability value	Environmental	Economic	Economic
	Value proposition	Service-centric	Service-centric	Service-centric
	Value creation	Delayed	Delayed	Instantaneous
	Dependency	Dependent	Dependent	Dependent

Urban areas' rapid growth and significance have spurred considerable interest in smart city solutions, presenting potential solutions for urban challenges such as waste disposal, energy demand reduction, and traffic congestion. As the examples demonstrate the wide range of smart city solutions, we need a categorization (i.e., a taxonomy of smart city solutions). The developed taxonomy combines technical and nontechnical aspects, and considers diverse subfields of smart cities, adding to the descriptive smart city research knowledge (Ahmed et al., 2016; Christmann et al., 2022; Nagel & Kranz, 2020; Vasudavan & Balakrishnan, 2019). It offers high-level insights through clustering, enabling focused research on specific smart city clusters and forming the basis for future theoretical work, for instance, developing theories to explain smart city solutions' effects (Type II theory) (Gregor & Hevner, 2013). For instance, Marrone and Hammerle (2018) found that citizens tend to be underrepresented in discussions on smart cities. Future research could lever the results to differentiate what positive and negative effects arise from which smart city solution types and related characteristics, examining their impacts on the citizens and on the city. The taxonomy transforms features into measurable dimensions, allowing for consistent and particular terminology in the research. It provides urban planning professionals and consultancies with a toolset for analyzing and classifying existing smart city solutions, enabling decisions on improvement and comparisons across cities. It has proven to be valuable for redesigning and developing solutions, unlocking potential for new offerings and city-wide implementations. It also helps match solution characteristics with end-user needs and owner constraints, providing design and implementation recommendations. This knowledge is crucial for urban planners in developing countries who are grappling with rapid urbanization challenges and limited capabilities.

Article #2 sheds light on IIoT startups. Similar to article #1, it illuminates a specific subfield of IoT; in this case, it combines IIoT with the dynamics of startups. As noted in the introduction, the IoT has immense potential, but the industrial sector lags behind expectations compared to the consumer sector. Large industrial companies find it much more challenging to integrate new technologies into their portfolio, which is why startups find it easier to do so (Criscuolo et al., 2012). Thus, IIoT startups are indispensable partners in the digital transformation of incumbent industrial companies, since they often supply the needed innovative IIoT solutions. Article #2 examines how IIoT startups can be classified and described, following a similar approach as article #1. To achieve this goal, a taxonomy for IIoT startups is developed. Nickerson et al.'s (2013) taxonomy development process guided the approach, which involved four iterations. The process began with a conceptual-to-empirical iteration, drawing on thematically similar taxonomies as a foundation. Three empirical-to-conceptual iterations are then conducted, levering data from 78 IIoT startups sourced from Crunchbase to refine and develop the taxonomy. Table 3 illustrates the comprehensive taxonomy, which spans 10 dimensions and their associated characteristics across the *solution*, *data*, and *business model* layers. The table also denotes whether each dimension is exclusive or non-exclusive. The amalgamation of these dimensions, along with their various characteristics across the three layers, forms the multilayer taxonomy for IIoT startup solutions. This taxonomy serves as the groundwork for developing a theory to analyze and classify IIoT startup solutions (Gregor & Hevner, 2013). Table 3 illustrates and subsequent sections delve into the taxonomy's dimensions and their characteristics.

Table 3: Taxonomy of IIoT Startup Solutions

	Dimension	**Characteristics**					
Solution	*Solution focus*	connecting	monitoring	controlling	optimizing	securing	N
	Personalization	not personalized	personalized				E
	Hybridization	product	service				N
Data	*Data source*	none	existing	new			E
	Time horizon	none	current	predictive			E
	Analytics	none	basic	extended			E
Business model	*Value proposition*	thing-centric	service-centric	platform-centric			E
	Business relationship	short-term	long-term				E
	Business cooperation	standalone	third-party integrable				E
	Pricing	single payment	consumption-based	subscription-based			N

E = exclusive dimension (one characteristic at a time); N = non-exclusive dimension (potentially multiple characteristics observable at a time).

The *solution* layer describes the core of IIoT startup solutions and has three dimensions. The solution focus delves into distinct functionalities such as connecting isolated industrial devices, monitoring conditions, controlling devices, optimizing performance through analyses, and ensuring data security (Paukstadt et al., 2019). Personalization distinguishes between standardized solutions and those tailored to individual client needs (H. Gimpel et al., 2018). Hybridization explores the diverse combinations of products and services offered by IIoT startups, ranging from standalone products to services and combined product-service offerings (Y. Park et al., 2012). The *data* layer delves into how IIoT startups lever data, as many IIoT startups rely on data use to provide comprehensive solutions (ur Rehman et al., 2019). Given data's crucial role in IIoT solutions, the dimension data source elucidates whether existing customer data sources are utilized, new sources are incorporated, or no data is required for the IIoT startup. Time horizon categorizes data into none, current, and predictive, indicating the relevance of time in an IIoT startup solution (H. Gimpel et al., 2018). Analytics classifies the analytical elements into none, basic (descriptive data usage), and extended (diagnostic, predictive, prescriptive data usage). The *business model* layer details the underlying business logic. Value proposition differentiates between thing-centric, service-centric, and platform-centric approaches, shaping an offering's core element (Püschel et al., 2020). Business relationship distinguishes between short-term and long-term engagements with an IIoT startup, while business cooperation classifies solutions as standalone or third-party-integrable based on their compatibility with external services (Lusch & Nambisan, 2015). Finally, pricing models are identified using Osterwalder and Pigneur (2010), encompassing single payment, consumption-based, and subscription-based models.

This taxonomy contributes to the descriptive understanding of the IIoT startup phenomenon, delving into a research field that has been under-explored and providing a foundation for researchers to build further theories. This includes deriving archetypes and theories for analyzing or explaining IIoT startup solutions (Gregor & Hevner, 2013), allowing one to understand higher-order configurations and anticipate trends in the IIoT and related industries. The taxonomy provides an overview over relevant characteristics and forms the basis for researchers evaluating IIoT startups. It also serves as a valuable tool for stakeholders in the IIoT field. It offers transparency for industrial companies seeking IIoT partners, facilitating the implementation of IIoT initiatives. The taxonomy enables the analysis of diverse solutions provided by IIoT startups, such as identifying third-party-integrable solutions. The taxonomy is a foundation for IIoT startups that seek to gain market overviews, identify niches, and assess their market potential. It sheds light on areas in the IIoT field that have remained inadequately addressed. It also helps one to better understand the IIoT startup phenomenon, identifying core solutions and defining typical solution characteristics.

Both of the developed taxonomies structure a subfield of IoT and offer the possibility to develop new IoT solutions on this basis because the taxonomies provide among others an impression of which solution possibilities already exist, what the distribution looks like, and which gaps exist. These taxonomies also show the possibility of cooperating with other companies (e.g., startups) and forming partnerships.

2 Conceptualization and Implementation

Once the analysis and idea development phase has been completed, the next step is conceptualizing, prototyping, and implementing solutions. As challenges also arise here, working through this topic area makes sense. In articles #3 and #4, software architectures for an IoT solution are developed as the main artifacts in each case to derive recommendations for action and enable subsequent prototyping and implementation based on the software architecture.

Article #3 extends the current knowledge and adds design and diagnosis insights regarding descriptive and prescriptive knowledge for smartphone-enabled PdM. PdM holds vast potential, particularly in the manufacturing industry, as it promises to reduce maintenance costs, raise machine uptime, and increase machines' lifetimes (Kang et al., 2016; Mobley, 2002; Schleichert, 2017). In contrast to preventive and reactive maintenance (Stenström et al., 2016; Swanson, 2001), PdM offers automated recommendations for production machine maintenance demands before unforeseen breakdowns or tool breakages occur (Mobley, 2002; Schleichert, 2017; Swanson, 2001). Yet PdM requires sensor data from machines – a challenge for enterprises, as a majority of the machines that are currently in use were manufactured and installed in a time before sensors or system logs (J. Lee et al., 2013). While production machines are now being equipped with internal sensors and interfaces for predictive analysis purposes (Roy et al., 2016), older operational production machines in good condition require external technologies to collect data (Civerchia et al., 2017; Groba et al., 2007; Mobley, 2002). One possibility for collecting data is equipping production machines with external sensors and connecting these sensors to an enterprise-wide network (Yoo et al., 2010). However, such retrofitting is cost-intensive and therefore not for everyone, especially not for small and medium-sized enterprises (SMEs). One possibility to minimize cost-intensive retrofitting is the use of retail smartphones. As handheld devices equipped with a vast array of sensors, smartphones offer a scalable option for manufacturers to gather machine data, make predictions, and present these predictions directly to users via the smartphone display (Chatterjee et al., 2018; Legner et al., 2017). The use of retail smartphones for PdM machines without or with limited existing built-in sensors or system logs offers an alternative to more expensive retrofits of existing machines, and smartphones could be used for multiple machines, making them especially interesting for low-resource SMEs. Thus, smartphone-enabled PdM solutions are being developed that have a software architecture and complementary reference processes for implementation and usage, prototype instantiations, and test installations.

For artifact development, article #3 follows the DSR paradigm suggested by Peffers et al. (2007), together with five manufacturing SMEs and a software developer. First, 12 company-specific use cases are identified, which serve as a foundation for developing a software architecture. Each of the manufacturers operated in different manufacturing industry areas (e.g., automotive supplier, spring manufacturing, or polymer solutions), which ensured transferable and generalizable results. For instance, one use case is monitoring the squeegee eccentrics in edge rail production. The smartphone sensors (e.g., a microphone, vibration sensors, and a magnetometer) monitor the squeegee eccentrics to predict outages. An outage leads to the possibility of particles being stuck on the edge rails, resulting in defective parts being produced. The squeegee eccentric is covered in oil and lacquer, but the drive unit allows access and possible placement for the smartphone for monitoring. As a next step, a software architecture is developed, enriched with two referential processes for implementing and using the software. Further, the artifacts are evaluated by building a prototype based on the architecture in close cooperation with the manufacturers.

The software architecture (Figure 2) seeks to show which software components are necessary for smartphone-enabled PdM, which tasks they fulfill, and how they interplay. It shows the individual software components that compose a *mobile application* and a *software application*, as well as their different layers and interfaces and how they interact with one another. The architecture is based on a three-layer software architecture model (i.e., presentation, application, and data) and is designed as a Unified Modeling Language (UML) component diagram consisting of components, possible subsystems, and required as well as provided interfaces (Fowler, 2010; Sommerville, 2016). The architecture and framework for the analysis and design of software architectures (Angelov et al. 2012) serve as the structural foundation.

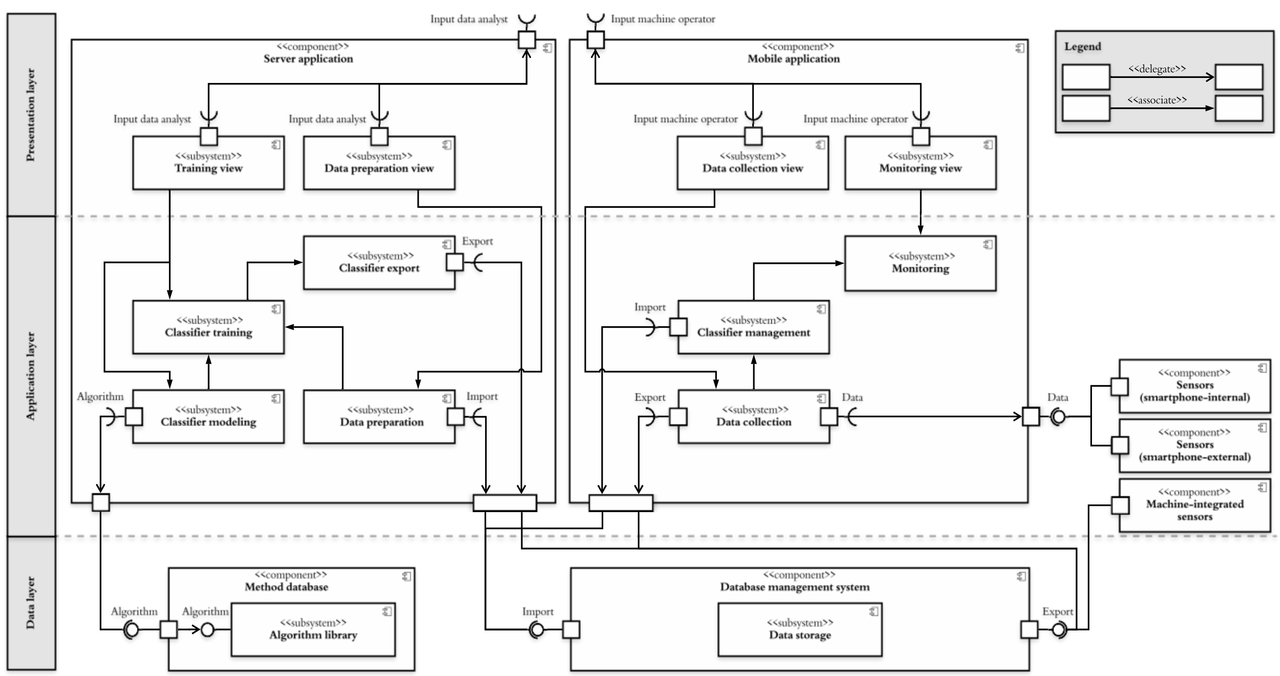

Figure 2: Software Architecture for Smartphone-Enabled Predictive Maintenance

The software architecture has two main parts: the *mobile application*, which runs on a mobile device (e.g., a smartphone), and the *server application*, which runs on a server. The mobile application collects datasets and uses sensor information data with a trained classifier to classify the status of the examined machine. The server application is used to train and update the classifier. The datasets are transferred to the server, and the classifier is trained with the datasets. After the training, the trained classifier is transferred to the mobile application, which can be used for classification directly on the shopfloor. The mobile application has five subsystems, including two graphical user interfaces (a data collection view and a monitoring view) and three functional subsystems (data collection, classifier management, and monitoring). The data collection subsystem orchestrates the distribution and management of collected data, requiring user input to initiate and define the collection function. It interfaces with both internal and external smartphone sensors, the latter accessed through options such as Bluetooth or near-field communication (NFC), extending the range of available sensors based on users' needs. The data collection subsystem also facilitates the exporting of acquired data to external or cloud storage for broader accessibility. Machine operators can select monitored production machines and can set parameters in the data collection view, making the smartphone versatile across multiple cases and machines. The classifier management subsystem provides an interface for importing data from machine-integrated sensors and trained classifiers via database connections. It preprocesses and analyzes data from both data collection and the database, using trained classifiers – machine learning (ML) – to generate predictions based on newly collected datasets. The monitoring subsystem uses the prepared data and chosen algorithms to train and test classifiers. The monitoring view receives input from the machine operator, selects the production machine, and provides defined output predictions based on predetermined parameters from the implementation process. The server application consists of six subsystems, including two graphical user interfaces in the presentation layer (a training perspective and a data preparation perspective) and four functional subsystems in the application layer (data preparation, classifier modeling, classifier training, and classifier export). The server application facilitates processing datasets, employing algorithms for analysis, and preparing the results for exporting. The ML data analysis components are integrated into smartphone-enabled PdM. The data preparation subsystem imports and preprocesses datasets, offering interfaces for both database imports and user input for setting criteria. The second subsystem, classifier modeling, allows the data analyst to specify classifier parameters, while the classifier modeling subsystem builds the defined classifier. The classifier training subsystem then conducts the necessary training steps, providing a ready-to-use classifier for real-time analysis when transferred to the mobile application. Finally, the classifier export subsystem transforms the classifier into a standardized data format that is compatible with various applications and consistent with the mobile application. Together, all these software components build the software architecture for smartphone-enabled PdM. The advantage of the structure of components and subsystems is that these can also be updated or exchanged individually; also, already existing software components can be used. For instance, smartphones already offer existing libraries for data storage management. Further, research streams already focus on algorithm selection and functionality, which can then be integrated into the classifier.

A software prototype is developed for smartphone-based PdM to evaluate the architecture in real-world settings and provide an initial, lightweight instantiation. The mobile application is constructed using the widely-used standard Java and operates on Android smartphones with Android 9 (Pie) as the operating system. Built with Python, the software application operates on a PC with Windows 10. The prototype is tested using a squeegee eccentric use case, yielding 613 datasets. Of these, 80% are utilized for supervised classifier training, resulting in 490 sets for training and 123 for testing. The overall training accuracy is $meanacc_{train} = 0.9606$ ($maxacc_{train} = 0.9837$, $SD_{train} = 0.0164$), with testing accuracy $meanacc_{test} = 0.9553$ ($maxacc_{test} = 0.9837$, $SD_{test} = 0.0316$). Further, the trained classifier is exported to the smartphone, integrated into the mobile application, and tested with new datasets, achieving 95% accuracy across 20 different sets. This prototypical implementation underscores the utility of the developed software architecture.

This article proves the possibility of utilizing smartphone-enabled PdM and contributes to research and practice. First, it combines justificatory knowledge from PdM (J. Lee et al., 2013; C. Park et al., 2016) and retail smartphones as monitoring devices (Chatterjee et al., 2018; H. Gimpel et al., 2019; Staacks et al., 2018). Second, through collaboration with manufacturers and a software developer, it demonstrates and evaluates the necessity of the proposed components, showcasing their ability to interact and yield reliable maintenance predictions. Twelve use cases are presented as examples of smartphone-enabled PdM, serving as applications developed in conjunction with manufacturers (for the complete list, see research article #3). However, the software architecture and corresponding processes are not limited to these cases. They can easily be transferred to other use cases and production contexts. Third, the article introduces a lightweight and affordable PdM solution to lever the low investment costs associated with retail smartphones, which are already ubiquitous. Thus, it extends the knowledge in the lightweight PdM approaches field (Mobley, 2002). The software architecture and reference processes empower manufacturers to develop a prototype for smartphone-enabled PdM that can efficiently monitor production machines. These artifacts facilitate the transfer of a prototype to diverse use cases and production machines. By considering and integrating interfaces into the software architecture, manufacturers can utilize existing infrastructure and tap into new data sources for further data analytics initiatives. Smartphone-enabled PdM offers opportunities to expand the use of digital technologies in the industrial sector and supports SMEs in digitalization.

In article #4, the research approach is applied to a different field, IoT applications in healthcare. As in the industrial environment, IoT has received much attention in healthcare, especially in the consumer sector, and many new applications can be found, such as smartwatches with health sensors or digital patent files. A wearable IoT system for continual bladder level monitoring in cooperation with the startup inContAlert is developed as a primary artifact. Wearable IoT systems enable real-time monitoring of physiological parameters (Jiang & Cameron, 2020), which is also beneficial for patients with neurogenic bladder dysfunctions (Manack et al., 2011). These patients face bladder control challenges owing to nerve damage, leading to health and psychosocial issues (Nseyo & Santiago-Lastra, 2017). Current solutions, such as diapers or timed catheterization, are imprecise and/or bulky (Hou & Rabchevsky, 2014; Vinod et al., 2019). While at this point, traditional medical care has reached its limits, the collection of physiological parameters through wearable IoT systems can contribute to patients' health and well-being by integrating continual bladder level monitoring into patients' daily lives, potentially improving their quality of life by preventing involuntary voiding and bladder distension (Fong et al., 2018; Molavi et al., 2014; Nseyo & Santiago-Lastra, 2017). With this in mind, the DSR approach is followed (Peffers et al., 2007). As a first step, a set of design principles (DPs) is developed. The software architecture for a continual bladder level monitoring system (BLMS) is then developed based on these DPs. It undergoes evaluation in a four-step evaluation approach grounded in the FEDS (Venable et al., 2016). This evaluation includes workshops with healthcare technology experts, interviews with patients and doctors, a prototypical implementation of the software architecture, and a field study, including the application of the prototype with patients.

As noted, in the first step, a set of DPs is developed, which is used further for the design specifications and the development of the software architecture (Figure 3).

Problem setting

- Patients lack an internal trigger to determine the moment for micturition
- Patients' limited well-being, risk of physical damage, and psychological burden
- Patients lack sensation and control over the bladder
- Patients miss knowledge about the current filling level
- Only bulky solutions for bladder level monitoring in stationary use
- No suitable bladder level monitoring solutions for daily use exist
- Need for individualized solutions for bladder level monitoring owing to the uniqueness of bladder form and function

Design principles

DP1. Principle of hybrid trigger: *IoT-based health monitoring systems should incorporate a hybrid trigger that includes both a facilitating and a spark trigger and builds on the integration of physiological signals that enable patients to perform a timed action.*

DP2. Principle of non-invasiveness: *IoT-based health monitoring systems should provide simple, non-invasive monitoring methods to foster patients' comfort during use and to avoid risks of health damage.*

DP3. Principle of sensor fusion: *IoT-based health monitoring systems should use a variety of sensors and merge the collected data to ensure accurate, precise, and contextualized measurement of the activity to be monitored.*

DP4. Principle of actionable information: *IoT-based health monitoring systems should provide actionable information that guides patients in performing precisely timed actions.*

DP5. Principle of individualization: *IoT-based health monitoring systems should include individual characteristics of patients and learning capabilities to provide an accurate model of the patient for actions to be monitored.*

Design specification

- Hybrid trigger, including phone notification based on measuring near-infrared spectroscopy (NIRS) data in the bladder (DP1, DP4)
- Measuring bladder level with non-invasive NIRS methods (DP2, DP3)
- Analyzing human data using ML in real-time (DP3, DP5)
- Combining data from NIRS, acceleration, and temperature (DP2, DP3)
- Provision of precise recommendations on when to perform a micturition (DP1, DP4)
- Consideration of individual patient characteristics, such as weight, height, gender, skin colour (DP5)

Figure 3: Overview over the Problem Setting, Design Principles, and Design Specification

As DP 1 is a new theoretical concept that extends existing theory, it will now first be presented in some detail. Among others, this article seeks to induce behavior change in neurogenic bladder patients, utilizing behavior theory as a theoretical lens (Fogg, 2009). Fogg's theory highlights motivation, ability, and triggers as the key factors that influence behavior change (Chatterjee et al., 2018; Pinder et al., 2018). Patients require motivation, ability, and appropriate triggers to achieve precisely timed micturitions. Fogg's triggers address varying motivational elements (Fogg, 2009). Neurogenic bladder patients who lack physiological signals necessitate facilitating triggers to interpret bladder data. Psychological issues and social stigma underscore the importance of addressing patient motivation (Nseyo & Santiago-Lastra, 2017). As fear of bladder damage and social rejection can motivate patients, a trigger system that integrates physiological data is crucial, surpassing conventional methods such as timers (Hou & Rabchevsky, 2014). For precise timing of micturition, one must consider the current bladder level and integrate it into the trigger mechanism. Combining various behavioral factors such as ability and motivation as well as integrating physiological signals, this established trigger represents a hybrid approach. A hybrid trigger that integrates physiological signals is proposed for IoT-based health monitoring systems, resulting in DP 1: *IoT-based health monitoring systems should incorporate a hybrid trigger that includes both a facilitating and a spark trigger and builds on the integration of physiological signals that enable patients to perform a timed action.* The other DPs deal with topics such as non-invasiveness, the combination of different sensors, the utilization of results to make clear recommendations to patients, and the individual adaptation of the system to patients (for a full explanation of the DPs, see research article #4).

With these DPs in mind, a software architecture is developed consisting of three main systems: a sensor box, a mobile application, and a server application. The sensor box records data on the bladder level and sends it to a mobile application located on a smartphone. While the bladder level increases, the sensor box continually transmits the data to the mobile application via Bluetooth. Patients can view their bladder level and the time remaining until their next micturition. The mobile application includes ML models that analyze the sensor data and predict the current bladder level. These ML models are trained on a server application and are transmitted to the mobile application. Patients receive a notification on their smartphone shortly before the bladder reaches a pre-defined, critical level. The sensor box is attached via an elastic band or a belt on the patient's skin and can be taken off at any time. As the sensor box and the mobile device are portable, patients can monitor their bladder level at any time and anywhere, and are not dependent on stationary bladder level monitoring devices at clinics or medical practices. Figure 4 presents the software architecture, designed as a UML component diagram (Fowler, 2010).

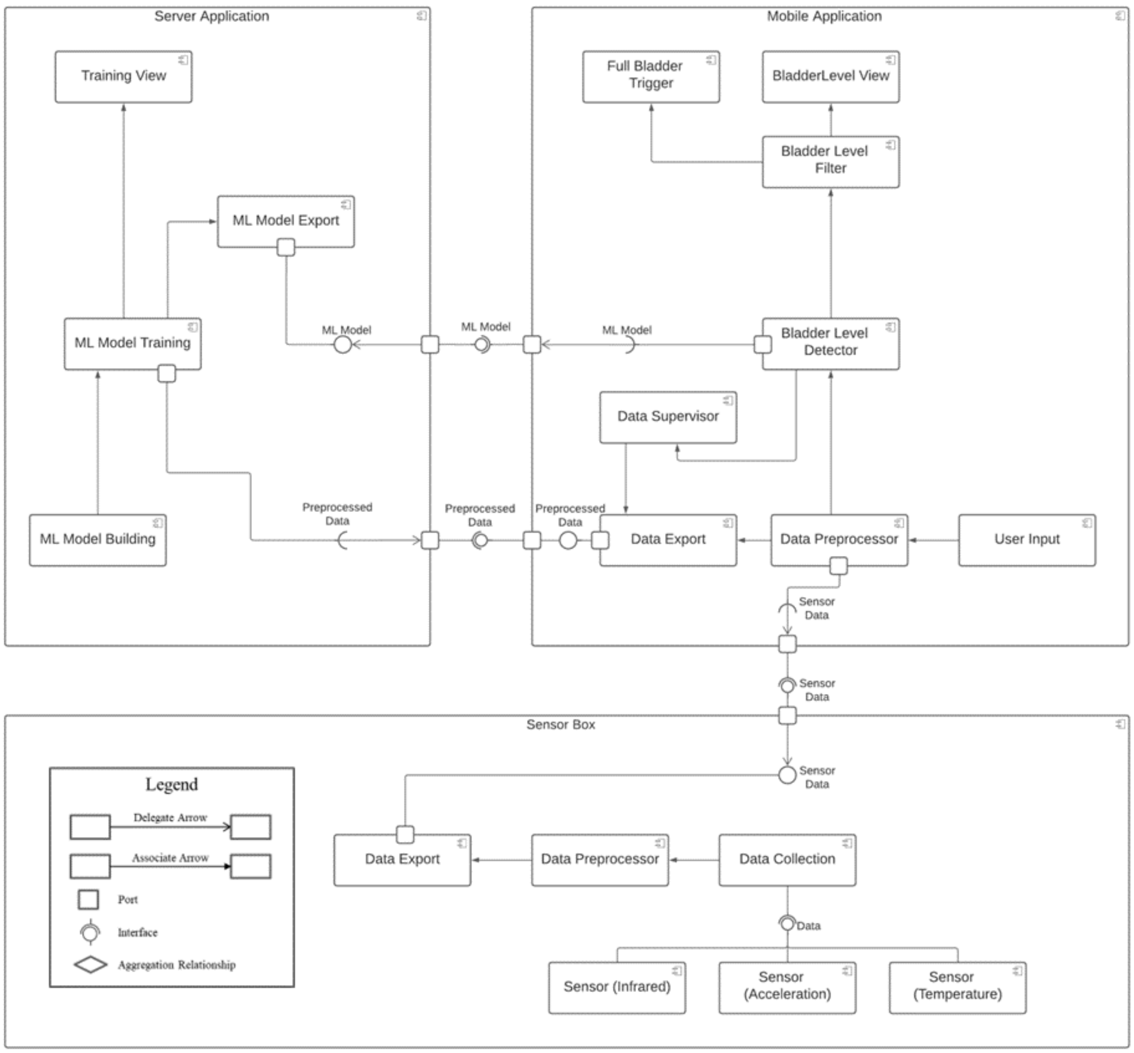

Figure 4: Software Architecture for a Wearable IoT-Based Health Monitoring System

The sensor box functions as the data generator, preprocessor, and exporter to the mobile application, housing infrared, acceleration, and temperature sensors. It is positioned approximately 2 cm above the pubic bone to continually collect physiological data related to the bladder level. The data preprocessor in the sensor box minimizes the data volume prior to transmission to the mobile application, conserving the mobile device's battery. Data packets are sent to the mobile application at fixed intervals. The mobile application acts as a data analysis unit and liaises between the sensor box and the user. It receives data packets wirelessly from the sensor box, conducts further preprocessing, and incorporates user-inputted individual characteristics. The bladder level detector assesses the preprocessed data to determine the bladder level, using a bladder level filter to rectify potential inaccuracies before displaying them to the user. Further, the mobile application includes a full bladder trigger for timely micturition notifications and a data supervisor to detect false detections and initiate ML model retraining on the server application. ML models on the server application are initially trained and continually updated using data from both the sensor box and the mobile application. The server application combines model building, training, and exporting components, allowing data analysts to define parameters, train models, and export them to the mobile application. It also provides a training view interface for analysts to monitor and manage the model development.

Following the design of the software architecture in a combined evaluation process, consisting of developing and testing a prototype and conducting 27 interviews with patients, doctors, and health tech experts. For the prototype testing, datasets on micturition cycles are collected. One micturition cycle is the span from an empty bladder to the micturition point. The urine volume per cycle is quantified as a key feature for training the ML model. Each cycle is assumed to exhibit linear bladder filling, with data labeled based on recorded micturition amounts in the mobile app. Each cycle's data is segmented into fixed five-minute windows to ensure consistent input for the ML model. The analysis uses a sliding window approach, predicting the bladder level one second ahead using a five-minute window. Input data has 26 features (i.e., 15 LED sensors, four acceleration sensors, a temperature sensor, elapsed time, micturition volume, age, BMI, sex, and skin color) encompassing LED emissions captured by detectors. A total of 919 micturition cycles are utilized: 44.8% for training (412 cycles), 50.2% for testing (462 cycles), and 5% for validation (45 cycles). Figure 5 presents one exemplary dataset (orange), matched with the ML prediction (light blue).

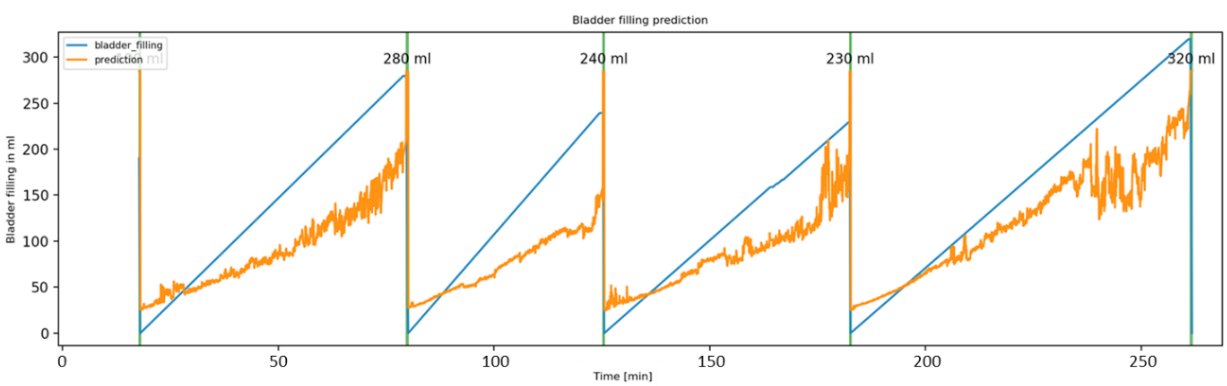

Figure 5: Exemplary Prediction Results

The examples demonstrate that the ML model could predict well, even with the low test samples. Utilizing the gathered data and the selected input features, the ML model attains a mean absolute error of 110.66 ml in forecasting bladder levels. Underestimations ranging from 80 to 120 ml are deemed safe for typical bladder capacities of 400 to 600 ml, minimizing the risk of bladder over-distension (Madersbacher et al., 2012). These prediction outcomes offer valuable insights for navigating neurogenic bladder dysfunction, ensuring prudent bladder management without jeopardizing one's health due to potential underestimations of the bladder level. These results align with the feedback received during the interviews. The patients confirm that the BLMS enhances their quality of life and health by providing knowledge of the bladder level, facilitating their daily activities and social participation, and mitigating their health risks. Patients express motivation to use the BLMS owing to fears of health issues and social rejection, highlighting its psychological benefits. The system effectively prevents bladder overfilling, reducing dependency on medication and catheterization frequency, and the non-invasiveness of the bladder level measurement is crucial to avoiding health risks associated with invasive procedures. Patients find the BLMS to be user-friendly and easily integrated into their daily routines, contrasting with more cumbersome and costly alternatives such as ultrasound-based solutions restricted to clinical settings.

The article also contributes to theory and practice. It addresses the deficiency of technological solutions for enhancing the self-management of neurogenic bladder patients by designing a wearable IoT-based BLMS. First, the BLMS represents a disruptive approach for addressing bladder dysfunctions by integrating physical sensors and advanced data analytics to supplant human bladder sensing. Further, the innovation of this approach is its integration of medical and IS knowledge, enriching understanding at the intersection of the two domains. Second, the software architecture contributes to DSR knowledge by providing an innovative solution for improving bladder dysfunction management (Chatterjee et al., 2018; Zadeh et al., 2021). With a focus on enhancing self-management, this article presents a disruptive approach by combining physical sensors and advanced data analytics to replace human bladder sensing, thereby filling a crucial gap in the healthcare domain. Third, it provides prescriptive knowledge by formulating DPs for IoT-based health monitoring systems applicable to neurogenic bladder dysfunction management. These principles offer valuable insights that can be extended to various healthcare applications, such as non-invasively monitoring neurogenic pulmonary edema or blood glucose levels, empowering patients and increasing their control over their health (Busl & Bleck, 2015). Fourth, it extends behavior theory by introducing a novel trigger type that integrates real-time physiological information (Fogg, 2009). This hybrid trigger concept, which combines internal physiological signals and external notifications, can potentially induce health-promoting behavior change, as demonstrated in the BLMS. The BLMS also offers a practical solution to the challenges faced by neurogenic bladder patients, reducing health and psychosocial risks while enhancing self-management. By providing concrete design specifications and a systematic software architecture, the research facilitates the implementation of the BLMS and offers a replicable model for monitoring physiological parameters in chronic disease management.

In sum, articles #3 and #4 are excellent examples of developing artifacts through a DSR process. In both articles, software architectures are developed, but for different application fields – industry and health. They each extend the descriptive knowledge of IoT solutions, allow future research to build on them, and demonstrate the added value for each field by developing a prototype in combination with further evaluation steps, demonstrating a key contribution for practical application. These articles also have implications for research, as the theory is extended, for instance, by using a theoretical lens on trigger theory, i.e., Fogg (2009).

3 Value Assessment and Business Development

What follows is a focus on the value assessment and business development of IoT solutions. As presented in the previous sections, there are already a large number of application options for IoT solutions, especially in the consumer sector. Nonetheless, IoT still lags behind expectations, especially in the industrial sector (Nicolescu et al., 2018; Odusote et al., 2016). One of the reasons for this is how hard it is to monetize IoT solutions. Monetizing IoT solutions presents unique challenges owing to their distinct characteristics, particularly in industrial settings. While the development costs for IoT solutions are substantial and recurring, the costs for replication, distribution, and individual use are approaching negligible levels (Fichman et al., 2014). Further, creating value through IoT solutions involves combining physical products and digital services, engaging multiple stakeholders, and yielding diverse direct and indirect benefits (Del Giudice, 2016; Sheth, 2016). Traditional cost-plus pricing methods, commonly used by industrial companies, overlook the monetization potentials of IoT solutions, as they neglect the de facto value delivered to customers and associated stakeholders. Thus, IoT solutions require a novel value assessment approach that acknowledges their unique characteristics, encompassing physical products and digital services. I address this challenge in articles #5 and #6.

Article #5 contends that IoT solutions require a value-based monetization strategy, underlining the importance of comprehensively understanding the value generated by such solutions for customers (Kindström, 2010). The literature on the monetization of IoT solutions offers insights from a variety of perspectives. Wortmann et al. (2017) presented a broad overview over revenue models, while Lee and Lee (2015) developed a real-options framework for evaluating IoT investments' value. Fähnle et al. (2018) examined internal value generation in industrial companies. Despite the IS community's extensive exploration of IT's business value (Kohli & Grover, 2008; Melville et al., 2004; Otim et al., 2012; Sun et al., 2016), we still lack a systematic examination of IoT solution value creation. This article follows a combined research approach to develop a framework for assessing IoT solutions' value from the perspective of an IoT solutions provider in industrial contexts. It combines a structured literature review based on the principles of Webster and Watson (2002) as well as vom Brocke et al. (2015), and uses the results to develop a framework for how IoT solutions create value and identify concrete value levers. Further, the results are evaluated in real-world scenarios by working with five IoT solutions providers from various industrial contexts. Figure 6 presents the framework for assessing IoT solutions' value.

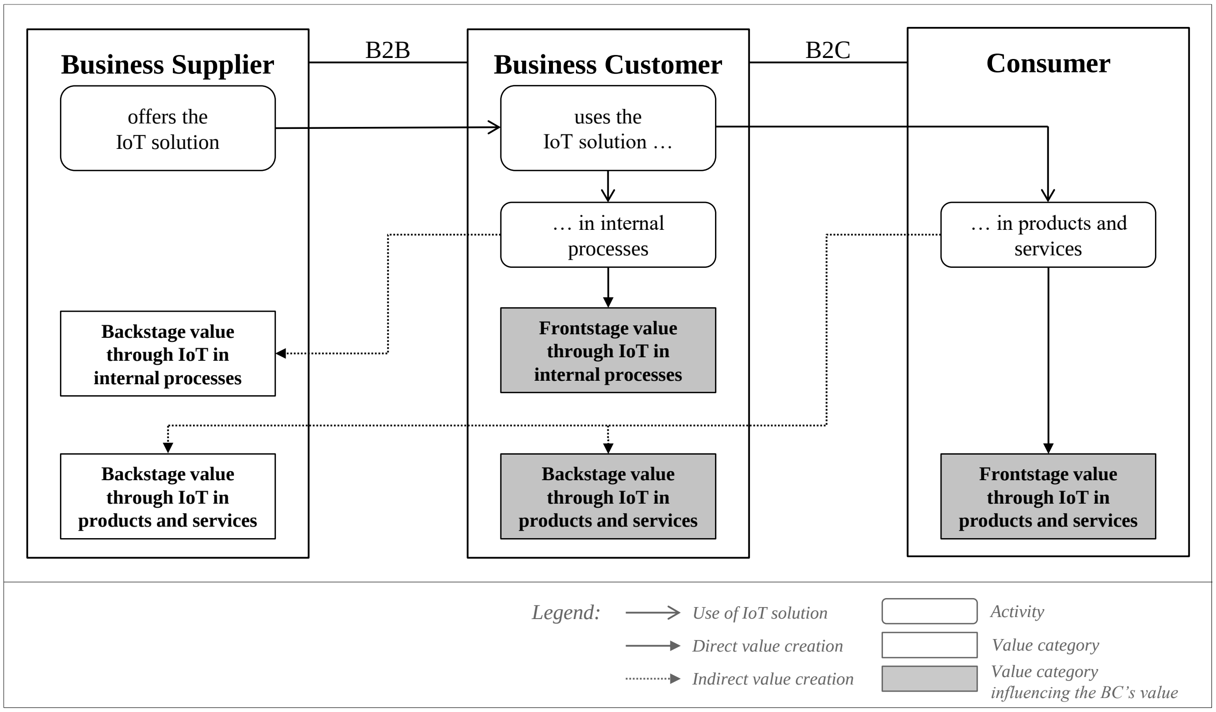

Figure 6: Framework for Assessing IoT Solutions' Value

The framework combines the concept of *frontstage* and *backstage* value (Beverungen et al., 2019) with a business-to-business-to-consumer (B2B2C) value chain. An IoT solution is used either in *internal processes* or in *products and services* (Fleisch et al., 2014; Nicolescu et al., 2018; Oberländer et al., 2018). Building on Beverungen et al. (2017) and Nicolescu et al. (2018) as justificatory knowledge from the IoT domain, IoT-related products – smart things – are boundary objects that facilitate value co-creation, that is, they create value on the side of IoT solutions providers and their users. Users derive frontstage value from product use through activities such as monitoring, optimization, remote control, and autonomous adaptation (Beverungen et al., 2019; Ostrom et al., 2015). Meanwhile, providers benefit from backstage analytics such as remote monitoring, diagnostics, data aggregation, analytics, and decision-making (Beverungen et al., 2019; Ostrom et al., 2015). Through ongoing customer engagement and insights from backstage analytics, providers can innovate in their offerings, positively impacting on future value generation (Siggelkow & Terwiesch, 2019).

This article also delves into how IoT solutions influence customer value in the framework's value categories to enhance practical applicability, offering specific value levers derived from a comprehensive literature review. The found value levers are structured along three value lever trees to assess frontstage value for consumers (Cs), business customers (BCs), and backstage value for BC. Each value lever tree has a first, second, and third level. Looking at an exemplary value lever tree, the value levers for frontstage value through IoT in internal processes (1st level) are structured along the seven types of waste (Hines & Rich, 1997; Melton, 2005). The found value levers in the literature range from *increasing the error detection rate* and *increasing the* *maintenance quality* (3rd level) as part of decreasing defects (2nd level), to *increasing just-in-time warehousing* and *location tracking* (3rd level) as part of reducing inventory (2nd level) (for the complete list of value levers, see research article #5).

This article contributes in multiple ways. First, it contributes to the existing knowledge on IoT and IoT-enabled business models (Almquist et al., 2016). The developed framework provides a conceptual understanding of relevant value categories and levers essential for identifying and evaluating specific value aspects of IoT solutions. First, the article transfers IT concept's business value onto IoT (Kohli & Grover, 2008; Melville et al., 2004; Schryen, 2013). While research into IT's business value initially focused on the internal company-level perspective to be gained through internal (process) improvements, the developed framework is informed by the recent understanding of IT as a part of products and services driven by digitalization (Ciriello et al., 2018; Kohli & Melville, 2019). Second, article #5 broadens the perspective from traditional business models to include IoT solutions' unique characteristics and value-creation mechanisms (Dijkman et al., 2015; Fleisch et al., 2014; Langley et al., 2021; Leminen et al., 2020). Fleisch et al. (2014), Suppatvech et al. (2019), and others found that a new way of thinking is required for IoT-related business models compared to traditional business models. The derivation of value propositions is a crucial first step for IoT solutions following a value-based pricing approach. By combining the perspective on IoT solutions' frontstage and backstage value (Beverungen et al., 2017; Nicolescu et al., 2018) with multiple stakeholders along the value chain, the developed framework facilitates a comprehensive assessment of an IoT solution's value, allowing the derivation of value propositions both internally and externally. This value assessment lays the foundation for developing monetization and commercialization concepts for IoT solutions. Third, the article provides a starting point for further theoretical and empirical studies of how IoT solutions affect both company performance and competitive advantage. While the article centers around BCs, it also conceptualizes additional value categories on the supplier side. In particular, the backstage value may lead to a competitive advantage through long-term insights and customer relationships (Kindström, 2010; van der Vegte, 2016). From a practical perspective, the developed framework undergoes real-world evaluation, involving interviews with representatives from several industrial companies and quantifying the value potentials of two IoT solutions. The practical implications include supporting IoT solution providers in structured value assessment, offering initial value levers for analysis, and guiding practitioners in applying the framework in specific contexts. By quantifying the value levers, practitioners can develop pricing and commercialization strategies, ensuring that they tap into their IoT solutions' full potentials. Positioned as a prescriptive framework, article #5 contributes to the prescriptive IoT knowledge, helping practitioners to assess IoT's value potentials.

Article #6 picks up precisely where the previous article ends. As analyzed in article #5, it is hard to assess IoT solutions' value. Although some first tools and frameworks assist with this challenge (Anke, 2019; Baltuttis et al., 2022; Linde et al., 2022), we still lack a structured method for assisting practitioners. Complementary to this, in their systematic literature review, Marx et al. (2020) revealed that most existing IoT-related methods focus on the design phase and less often on the value assessment phase. With this in mind, article #6 focuses on developing a method for assessing smart services' value.

At this point, the term *smart services* needs to be briefly defined. Allmendinger and Lombreglia (2005) pioneered the notion of smart services, introducing them as a novel category of services grounded in the machine intelligence inherent in smart products, characterized by their awareness and their connectivity. Expanding on this foundation, Beverungen et al. (2019) further elucidated the concept, drawing on service science's definition of service as *"the application of specialized competences (operant resources – knowledge and skills), through deeds, processes, and performances for the benefit of another entity or the entity itself"* (Vargo & Lusch, 2008, p. 26). They integrated this definition into the concept of smart products, recognizing their pivotal role in smart services through the provision of both awareness and connectivity (Allmendinger & Lombreglia, 2005). By definition, IoT solutions and smart services go hand in hand. However, while a smart thing is a central component and the focus of IoT solutions, the service concept is more in the foreground with smart service, even if both terms have IoT as their central concept.

Article #6 follows the DSR process to develop this method to assess smart services' value (Peffers et al., 2007). Situational Method Engineering is integrated into the design and development phase to tailor the DSR process to method development (Brinkkemper, 1996; Henderson-Sellers et al., 2014). Situational Method Engineering is a research method that structures the development of new and effective methods for specific situations (Henderson-Sellers et al., 2014). During the evaluation phase, the FEDS (see article #4) is employed for method evaluation (Venable et al., 2016) to ensure that the research is relevant and rigorous. Therefore, formative and summative evaluation episodes are implemented with real users from four manufacturing companies to ensure practical relevance.

Figure 7 presents an overview over the developed Value Assessment Method for Smart Services (VAMOS), which consists of three activities: 1) preparation and contextualization, 2) qualitative valuation, and 3) quantitative valuation.

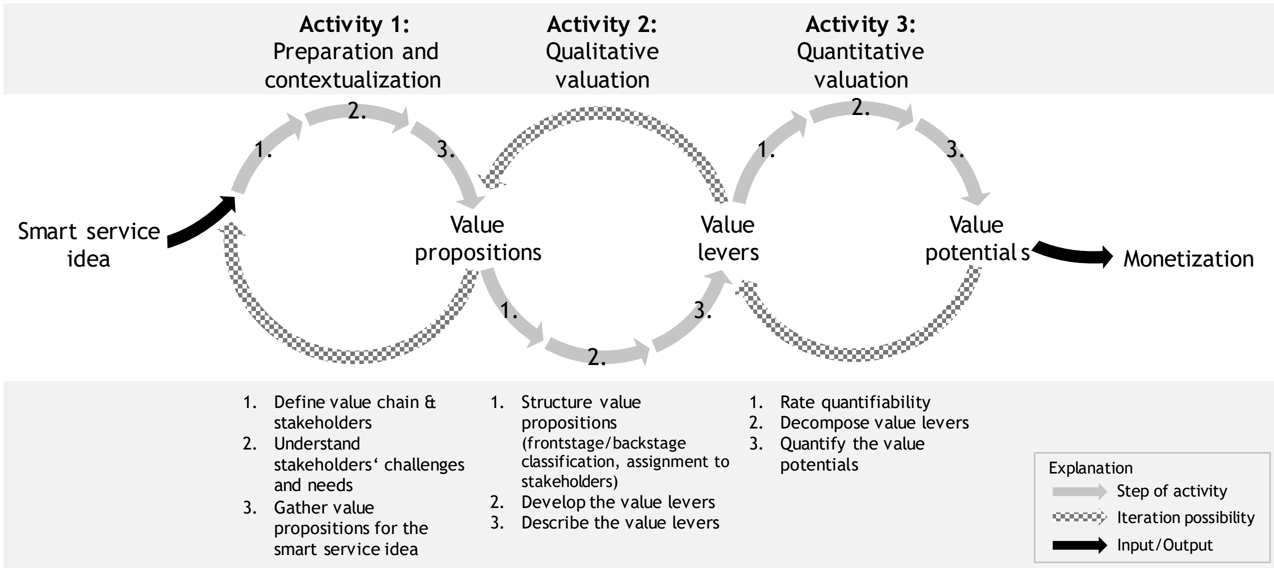

Figure 7: Overview over the Value Assessment Method for Smart Services (VAMOS)

Activity 1 serves as the cornerstone for subsequent activities by establishing a comprehensive understanding of the smart service at hand and the context in which the method user is operating. This initial phase focuses on grasping the value chain and identifying the relevant stakeholders – both BC and C – while delving into customer challenges and needs addressed by the smart service concept (Linde et al., 2022). From this understanding, the value propositions of the smart service idea are formulated. As outlined in the roles, method users facilitate interdisciplinary workshops across the company, engaging employees from various hierarchical levels to collectively explore customer challenges and needs in depth. Beyond internal perspectives, method users may enrich their innovation endeavors by incorporating external perspectives and involving customers through interviews or collaborative workshops (Brown & Katz, 2011; Katz & Allen, 1982).

Activity 2 entails the specification of value levers that are crucial for determining a smart service's worth. The objective is to organize and deepen the value propositions established in the previous activity. The value propositions are initially aligned with relevant value categories (frontstage and backstage) pertinent to various stakeholders. The value propositions are then disaggregated into distinct components – value levers – to facilitate a detailed understanding and enable more straightforward quantification in subsequent activities. Prioritization is a key element at this stage, focusing on selecting the three to five most relevant value propositions to streamline subsequent efforts and enhance overall clarity.

Activity 3 aims to quantify the potential value of selected and prioritized value levers. The method involves rating the quantifiability of value levers into categories ranging from nonquantifiable to well quantifiable. Even if deemed nonquantifiable, these levers provide valuable nonfinancial insights that support smart service sales and increase understanding in industrial companies. The subsequent step entails decomposing processes that underlie each lever to identify calculation factors for quantification, a process that facilitates understanding and estimation of smart services' value, which can be added up to calculate the total value potential for every stakeholder.

The developed method addresses the need for a structured approach to assessing smart services' value for industrial companies. Since VAMOS is, in part, a combination of existing fragments against the background of smart services, it corresponds to the DSR contribution type *exaptation*, i.e., the extension of known solutions to new problems (Gregor & Hevner, 2013; Sonnenberg & vom Brocke, 2012). It offers several contributions to theoretical knowledge and practice. First, it fills a gap in the academic research by providing a structured method for evaluating smart services' value, which existing approaches lacked (Anke, 2019; Baltuttis et al., 2022; Linde et al., 2022; Poeppelbuss & Durst, 2019). Second, article #6 provides a scientifically sound method that accounts for different stakeholders' value co-creation (frontstage and backstage) and builds on the concept of smart products acting as boundary objects (Beverungen et al., 2019). It extends the research in this field and especially addresses the research need pointed out by Nicolescu et al. (2018), who examined the emerging meanings of *value* in the IoT context through three analytical lenses: social, economic, and technical. In particular, article #6 addresses one of the major gaps in the economic perspective: the lack of reliable models for multimodal values and their interactions. Third, in line with article #5, it lays the groundwork for future research into strategies to monetize and commercialize smart services by emphasizing customer and supplier value and providing quantified value levers that can inform revenue models and commercialization efforts. In practice, VAMOS helps industrial companies to systematically assess smart services' value, offering step-by-step instructions and templates for implementation. It fosters interdisciplinary collaboration within companies and supports their transition from product-oriented to service-oriented businesses. By prioritizing customer-centric approaches, VAMOS helps transform traditional businesses in line with evolving market demands.

III. Conclusion

1 Summary

The IoT continues to have impacts in the consumer field and in the industrial sector. Equipping things with sensors and actuators and connecting them to the Internet has been associated with exponential growth and enormous economic potential. Starting with the consumer sector, smart things – for instance, voice assistants, fitness bracelets, and smart TVs – are an integral part of our lives. The IoT is gradually finding its way into industrial environments but still lags behind expectations. This doctoral thesis examines how the development of IoT solutions in different application areas can be supported and what is necessary to increase the dissemination of IoT, complementing the research into the technical design of IoT. This thesis focuses on the complete development process, i.e., on the phases 1) *analysis and ideation*, 2) *conceptualization and implementation*, and 3) *value assessment and business development.*

First, this thesis analyzes existing IoT solutions and presents two taxonomies on two separate fields – smart cities and IIoT startups. These taxonomies form both the foundation for future research to build on (for instance, focusing on explaining the status quo) and allow practitioners to find gaps in their portfolio and focus on bridging these gaps. Second, this thesis presents two software architectures. The first proves the applicability of IoT solutions for PdM in SMEs as a low-cost alternative and tool that supports the healthcare sector, while the second presents an architecture for wearable IoT-based health monitoring systems. As these software architectures are developed in close cooperation with practitioners, real-life practicability and usefulness are ensured. Third, this thesis takes on the business perspective of IoT solutions, developing a framework and then a method for assessing IoT solutions' value and supporting the complicated monetization of IoT solutions compared to more straightforward cost-plus pricing in the industry. This thesis expands the IoT research, since different artifacts are developed and new theoretical concepts and lenses are created, expanded, and/or transferred to new fields of application.

In Section II.1, on phase 1, *analysis and ideation*, two taxonomies are presented. Both articles follow Nickerson et al.'s (2013) taxonomy development process. Article #1 presents a taxonomy of smart city solutions. This application field for IoT solutions is extremely exciting, as demographic developments are predicted to lead to immense growth in cities (UN, 2018), which already require solutions to challenges such as increased traffic, energy consumption, and waste management. The article presents a taxonomy consisting of 10 dimensions based on the literature on smart cities as well as data from 106 smart city solutions. Further, article #1 presents three clusters (Ferreira & Hitchcock, 2009; Ward, 1963), allowing an additional grouping of smart city solutions. The taxonomy and the clusters convert features into quantifiable dimensions, establishing uniform and specific terminology within smart city research. It equips urban planning practitioners and consulting firms with a tool to evaluate and categorize current smart city solutions, facilitating decisions regarding enhancements and comparisons across different cities. Article #1 helps align solution attributes with end-user requirements and owner limitations, offering guidance for design and implementation. It also allows future research to build on the foundation, extending research in the direction of providing answers to the distribution of smart city solutions or explaining the development of smart cities. In article #2, the approach is transferred to the IIoT startup field. For emerging technologies like IIoT, startups have a crucial role, as new technologies are often first commercialized by startups. The article presents a taxonomy that analyzes and structures the wide range of startups in this field, contributing to the descriptive knowledge of the IIoT startup phenomenon. The taxonomy serves as a starting point for researchers to theorize further, for instance, to derive archetypes and theories for analyzing or explaining (Gregor & Hevner, 2013).

In Section II.2, on phase 2, *conceptualization and implementation*, two software architectures are presented. Both articles follow Peffers et al.'s (2007) DSR process, combined with Galster and Avgeriou's (2011) architecture development method. The developed architectures help distribute IoT solutions to other fields of application, i.e., PdM for SMEs and IoT-based health monitoring. In article #3, a software architecture is developed for smartphone-enabled PdM as the main artifact. The developed software architecture, combined with the processes for implementation and use, provides a low-cost alternative to implementing PdM in existing machinery. Developing a prototype and conducting evaluation interviews with five different manufacturers proved the smartphone-enabled PdM's applicability and usefulness.

Further, article #4 transfers the approach to IoT-based health monitoring. The IoT-based monitoring of physiological parameters promises rich opportunities to promote overall health and self-management of patients with chronic diseases, in this case, neurogenic bladder patients who lack sensation and control over their bladder. The article presents a software architecture tested with patients and evaluated with an additional 27 interviews. It contributes to the IS research through prescriptive knowledge for IoT-based bladder-level monitoring systems that can be transferred and generalized to similar application areas. Further, it contributes to behavior theory by theorizing a new trigger type called a hybrid trigger that translates physiological data into perceivable information and tells them the precise moment their bladder reaches a critical level (Fogg, 2009).

In Section II.3, on phase 3, *value assessment and business development*, this doctoral thesis takes an economic perspective on IoT solutions. As IoT solutions require a new perspective on value assessment compared to traditional physical products, articles #5 and #6 shed light on this challenge. Article #5 presents a framework for assessing IoT solutions' value. It combines the concept of frontstage and backstage value with the stakeholders of a typical value chain (Beverungen et al., 2019). It extends the existing theoretical foundation on IoT-enabled business models and provides practitioners with a concept for future monetization and commercialization (Agostini & Nosella, 2021; Almeida et al., 2020). Article #6 extends the framework. As valuable as the developed framework is, it lacks a structured application approach for practitioners. To fulfill this research need, a method for value assessment of smart services (VAMOS) is developed. Combining DSR and Situational Model Engineering, the method consists of three consecutive phases (Henderson-Sellers et al., 2014; Peffers et al., 2007). Besides providing practitioners with a structured approach, it extends the theoretical literature on smart services, addressing the research need regarding IoT's value (Nicolescu et al., 2018).

2 Limitations and Future Research

This doctoral thesis has limitations. The following section focuses on an aggregated overview over these limitations, opening opportunities for future research. For a detailed overview, please refer to each article's limitations.

First, a taxonomy always captures a limited period (Nickerson et al., 2013). The taxonomies developed in articles #1 and #2 build on the IoT literature as well as real-world IoT solutions data from the Crunchbase database. Considering the fast pace at which novel technologies – such as IoT – evolve, previously underrepresented characteristics will become more prevalent, and new characteristics will emerge. A revisit could help identify changes, allowing for a comparison as well as conclusions about the development of IIoT startups over time. Further, neither all smart city solutions nor all IIoT startups are considered in either taxonomy, as a random selection was made, which means that there is always the opportunity to expand the data foundation. Taking a step out of the taxonomies toward the *analysis and ideation* phase, the ideation of IoT solutions is not the focus of this doctoral thesis. Ideating potential IoT solutions is another complex stream that requires particular attention and which remains *"poorly understood"* (Kohli & Melville, 2019, p. 214). Thus, developing toolsets that support industrial companies in finding IoT solutions ideas and extending IoT innovation literature is another stream for future research (Nicolescu et al., 2018).

Second, moving on to the *conceptualization and implementation* phase, both developed software architectures have limitations. Both examine a specific problem and then abstract to a larger field of application, i.e., smartphone-enabled PdM and IoT-based health monitoring systems. In both cases, it would be stimulating to see the software architectures in a second prototype with an adapted field of use to validate the architectures (Galster & Avgeriou, 2011). Further, expanding the test phases and interviews could extend the artifacts' applicability (van Buskirk & Moroney, 2003). Both articles focus on the developed software architecture and leave the used ML algorithms for data processing for future research. Since both software architectures are modular, future research could compare different algorithms' effectiveness and could focus on data analysis comparison (Fechner et al., 2023; Kratsch et al., 2021). Further, the path from a software architecture to a finished, marketable product remains long; this falls outside the scope of both articles. Future research could focus on developing a toolset or guidelines for providing commercial products out of prototypes or, in a first step, can analyze whether the toolsets for traditional products also apply to IoT solutions (Sharma et al., 2019).

Third, articles #5 and #6 focus on assessing IoT solutions' value by presenting a framework and a corresponding method. These two artifacts lay the foundation for future monetization and commercialization (Fleisch et al., 2014; Langley et al., 2021; Leminen et al., 2020; Suppatvech et al., 2019). Future research could extend the value assessment and could focus on revenue model development for IoT solutions. A revenue model is made up of other factors beyond value, such as the competitive situation or cross-selling potentials (Linde et al., 2022). It would be worth looking at it as part of future research on developing a monetization strategy for IoT solutions. Further, the literature on business model development for IoT could be revisited (Fleisch et al., 2014) to examine how it has changed in the past decade.

This doctoral thesis focuses on developing individual IoT solutions and how this development can be accompanied and supported. The next step would be to move from unique standalone solutions to entire ecosystems and their interactions with one another. As the development of individual solutions can lead to fragmentation, it is crucial to keep an eye on the corporate ecosystem (Broring et al., 2017). Also, ecosystems offer further advantages, which could be worked out precisely for the IoT (Williamson & Meyer, 2012). Future research could extend the value assessment for IoT solutions to IoT ecosystems and could extend the B2B2C value chain to a network of partners and competitors.

Notwithstanding these limitations, I am confident that this doctoral thesis contributes to the body of knowledge on IoT solutions. It will guide researchers and practitioners in understanding, analyzing, and developing IoT solutions and overall extends the theoretical foundation of IoT solutions.

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V. Appendix

1 Index of Research Articles

Research Article #1: Illuminating Smart City Solutions – A Taxonomy and Clusters

Jonas C., Schmitt K., Oberländer A. & Ebel P. (2023). Illuminating Smart City Solutions – A Taxonomy and Clusters. Published in: *Proceedings of the 44th International Conference on Information Systems (ICIS), Hyderabad, India.*

(VHB-JQ3: Category A)

Research Article #2: Demystifying Industrial Internet of Things Start-Ups – A Multi-Layer Taxonomy

Jonas C., Oberländer A., Schmitt K. &. (2022). Demystifying Industrial Internet of Things Start-Ups – A Multi-Layer Taxonomy. Published in: *Proceedings of the 17th International Conference on Wirtschaftsinformatik, Nuremberg, Germany*.

(VHB-JQ3: Category C)

Research Article #3: Smartphone-Enabled Predictive Maintenance – Development and Implementation of a Reference Architecture and Processes

Jonas C., König U. & Röglinger M. (2022). Smartphone-Enabled Predictive Maintenance – Development and Implementation of a Reference Architecture and Processes. Published in: *IEEE Transactions on Engineering Management*.

(VHB-JQ3: Category B)

Research Article #4: Designing a Wearable IoT-Based Bladder Level Monitoring System for Neurogenic Bladder Patients

Jonas C., Lockl J., Röglinger M. & Weidlich R. (2023). Designing a Wearable IoT-Based Bladder Level Monitoring System for Neurogenic Bladder Patients. Published in: *European Journal of Information Systems.*

(VHB-JQ3: Category A)

Research Article #5: Conceptualizing and Assessing the Value of Internet of Things Solutions

Baltuttis D., Häckel B., Jonas C., Oberländer A., Röglinger M. & Seyfried J. (2022). Conceptualizing and Assessing the Value of Internet of Things Solutions. Published in: *Journal of Business Research.*

(VHB-JQ3: Category B)

Research Article #6: Value Assessment Method for Smart Services

Jonas C., Kuch F. & Oberländer A. Value Assessment Method for Smart Services. Under review: *Journal of Business Research.*

(VHB-JQ3: Category B)

2 Individual Author Contributions to the Six Research Articles

This doctoral thesis is cumulative, comprising six separate articles containing the main body of work. All the articles were developed in different teams with multiple authors. The various research settings and my individual contributions to each article were as follows:

Article #1 (Jonas et al., 2023a) was developed with three co-authors. While one collected the data, two of us developed the research method and scope. Further, two of us developed the taxonomy, conducted the cluster analysis, collected the evaluation data, and did the Q-sort evaluation. The two other co-authors joined during the submission and revision of the paper. I presented the paper at the *44th International Conference on Information Systems (ICIS)* in Hyderabad, India. One co-author and I were the leading (equally contributing) authors, while the other two were still involved throughout the project.

Article #2 (Jonas et al., 2022a) was developed by a team of four authors. All four jointly developed the scope and setting of the paper. Two co-authors collected the data for the taxonomy development, while all four of us developed the results together. I presented the paper at the *17th International Conference on Wirtschaftsinformatik* in Nuremberg, Germany. All four of us contributed equally to the paper.

Article #3 (Jonas et al., 2022b) was developed by a team of three authors. All four of us jointly developed a reference architecture and processes for implementing and using smartphone-enabled predictive maintenance. I conducted the underlying literature work and built the prototype for the evaluation, while all three authors developed and refined the artifact together. I was substantially involved in all parts of the research paper, and all three of us contributed equally to the paper.

Article #4 (Jonas et al., 2023b) was developed by a team of four authors. All four of us jointly developed the scope and setting of the paper. One did the data collection and the programming for the prototype, while all three of us wrote the paper together and revised it through submission. I was substantially involved in all parts of the paper, and all of us contributed equally.

Article #5 (Baltuttis et al., 2022) was developed by a team of six authors. Five of us jointly developed the article's basic concept. Together with one of the co-authors, I was responsible for revising the conceptual framework and for extending our model's evaluation with the five industrial companies through the submission process. Overall, we contributed equally to the article's content.

Article #6 (Jonas et al.) was written with two co-authors. I was the leading author responsible for the model development and evaluation. I designed the research approach, developed the VAMOS method, and related our work to justificatory knowledge. Further, I organized, prepared, and did the evaluations. Although the article represents, to a large extent, my work, the two co-authors were involved throughout the project and helped discuss and advance our contributions. This paper is currently under revision.

3 Research Article #1: Illuminating Smart City Solutions – A Taxonomy and Clusters

Authors:

Jonas C., Schmitt K., Oberländer A. & Ebel P.

Published in:

Proceedings of the 44th International Conference on Information Systems

Abstract:

With urban problems intensifying, Smart City solutions are recognized by researchers and practitioners as one of the most promising solutions to make urban areas economically, environmentally, and socially sustainable. While many elements of Smart City solutions have been explored, existing works either treat Smart City solutions as technical black boxes or focus exclusively on Smart City solutions' technical or non-technical characteristics. Therefore, to conceptualize the unique characteristics of Smart City solutions currently available, we developed a multi-layer taxonomy based on Smart City solution literature and a sample of 106 Smart City solutions. Moreover, we identified three clusters, each covering a typical combination of characteristics of Smart City solutions. We evaluated our findings by applying the Q-sort method. The results contribute to the descriptive knowledge of Smart City solutions as a first step for a theory for analyzing and enable researchers and practitioners to understand Smart City solutions more holistically.

Keywords:

Smart City, Smart City solutions, Taxonomy, Clusters, Sustainability

4 Research Article #2: Demystifying Industrial Internet of Things start-ups – A multi-layer taxonomy

Authors:

Jonas C., Oberländer A., Schmitt K. & Wethmar S.

Published in:

Proceedings of the 17th International Conference on Wirtschaftsinformatik

Abstract:

Described as a fundamental paradigm shift by researchers, the Industrial Internet of Things (IIoT) is credited with massive potential. In the context of emerging technologies, such as the IIoT, start-ups occupy a crucial role, as new technologies are often first commercialized by start-ups. Because of the rising importance of IIoT start-ups as drivers of industrial innovation, IIoT solutions demand deepened theoretical insights. As existing classification schemes in the industrial context do not sufficiently account for the ever more critical role of IIoT start-ups, we present a multi-layer taxonomy of IIoT start-up solutions. Building on state-of-the-art literature and a sample of 78 real-world IIoT start-up solutions, the taxonomy comprises ten dimensions and related characteristics structured along the three layers solution, data, and business model. The taxonomy contributes to the descriptive knowledge on the IIoT and enables researchers and practitioners to better understand IIoT start-up solutions.

Keywords:

Industrial Internet of Things, Industry 4.0, Start-up, Solutions, Taxonomy

5 Research Article #3: Smartphone-enabled Predictive Maintenance – Development and Implementation of a Reference Architecture and Processes

Authors:

Jonas C., König U. & Röglinger M.

Published in:

IEEE Transactions on Engineering Management

Abstract:

Predictive maintenance (PdM) is a hot topic in the field of manufacturing. However, its industry-wide realization lacks accepted integration concepts. Small and medium-sized enterprises (SMEs), in particular, tend to postpone PdM initiatives, primarily due to the high costs and effort of creating interoperability with established as well as in-use machines. PdM requires machine data to be proactively maintained. Therefore, in-use machines without integrated sensors must be replaced or cost-intensively upgraded. Furthermore, it is not advisable to invest in upgrades of existing machines, as they are cost-intensive, and their remaining lifespan is unknown as well as difficult to predict. One promising approach to applying PdM to these kinds of machines is the use of retail smartphones. With up to 16 sensors onboard, they offer an opportunity to cost-effectively collect required data without being tied to a single machine. Following a design science research approach, we present a reference software architecture consisting of a mobile and server application and reference processes for smartphone-enabled PdM to provide a lightweight approach, especially for SMEs. Together with five manufacturers and a software developer, we demonstrated and evaluated our artifacts using the software prototypes in a real-world setting.

Keywords:

Predictive Maintenance, Smartphone, Reference Software Architecture, Design Science Research, Prototype

6 Research Article #4: Designing a Wearable IoT-based Bladder Level Monitoring System for Neurogenic Bladder Patients

Authors:

Jonas C., Lockl J., Röglinger M. & Weidlich R.

Published in:

European Journal on Information Systems

Abstract:

Over the last years, the use of Internet of Things (IoT) systems in healthcare has increased due to technological advancements and increased availability of data. Sensor-based monitoring of physiological parameters, in particular, promises rich opportunities to promote overall health and self-management of patients suffering from chronic diseases. As such, neurogenic bladder patients lack sensation and control over their bladder while they could regain sovereignty over their bladder management through monitoring their physiological parameters. In this paper, we aim to develop a wearable IoT-based bladder level monitoring system for managing neurogenic bladder dysfunctions. We develop a set of design principles taking a stance from behaviour theory and implement the design principles in a software architecture following a design science research approach. Further, we evaluate and revise the developed artefact and implement a prototype of the software architecture. Our research contributes to IS research through prescriptive knowledge for IoT-based bladder level monitoring systems that can be transferred and generalised to similar areas of application. Further, we contribute to behaviour theory as we theorise a new type of trigger that we call a hybrid trigger.

Keywords:

Design Science Research, Internet of Things, Healthcare, Design Principles, Neurogenic Bladder

7 Research Article #5: Conceptualizing and Assessing the Value of Internet of Things Solutions

Authors:

Baltuttis D., Häckel B., Jonas C., Oberländer A., Röglinger M. & Seyfried J.

Published in:

Journal of Business Research

Abstract:

The Internet of Things (IoT) is associated with enormous economic potential. To date, however, actual revenues remain below expectations. This circumstance particularly affects IoT solution providers in industrial contexts where effective value assessment is critical for market success. Since a deeper understanding of how IoT solutions create value is required to address this challenge, we develop a framework and corresponding value levers for assessing the value of IoT solutions along an archetypical yet configurable business-to-business-to-consumer (B2B2C) value chain. Taking the perspective of an IoT solution provider in the industrial context, we evaluate the framework with five such solution providers and apply the value levers for an initial value quantification. Our work extends previous research and furthers knowledge on the business value of IT and IoT. It also supports practitioners in assessing IoT value potential.

Keywords:

Internet of Things; Business Value; Value Assessment; Value Creation; Framework; Value Levers

8 Research Article #6: VAMOS: Value assessment method for smart services

Authors:

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Extended Abstract:

Despite the enormous economic potential of smart services, their revenues often fall short of predictions and expectations (Odusote et al., 2016). Smart services radically change traditional business logics. Because of their different cost and revenue structure compared to traditional industrial products, a value-based commercialization logic is required instead of a cost-based one (Haaker et al., 2021; Paiola & Gebauer, 2020). This approach necessitates a profound understanding of the value created by smart services. As academia and practice have not provided a corresponding approach, we aim to answer the research question: *How to systematically assess the value of smart services?*

We developed the Value assessment method for smart services (VAMOS). As such, VAMOS is a structured and repeatable method that can be applied to different smart services and is a central building block in the overarching process from ideation to commercialization of a smart service. To develop VAMOS, we applied the design science research (DSR) paradigm to ensure theoretical and practical relevance (Gregor & Hevner, 2013; van Aken, 2004). Regarding the design and development of VAMOS, we chose situational method engineering (SME), which helps to develop appropriate methods for specific situations (Brinkkemper, 1996; Henderson-Sellers et al., 2014). To demonstrate VAMOS, we present the results of the method's application in four projects conducted with product-oriented industrial companies seeking to either offer smart services or extend their smart service portfolio. We applied the Framework for Evaluation in Design Science Research (FEDS) to evaluate the method (Venable et al., 2016). Thereby, we implemented several formative evaluation episodes informing the design of the method and summative evaluation episodes demonstrating VAMOS's ease of use, usefulness, efficiency, generality, and operationality (Sonnenberg & vom Brocke, 2012).

VAMOS provides step-by-step guidance and accounts for the characteristics of smart services to purposefully support organizations in assessing the value of their smart services. It combines three sequential activities: (1) Preparation & contextualization, (2) Qualitative valuation, and (3) Quantitative valuation. Activity 1 lays the foundation for further activities by creating a profound understanding of the smart service under investigation and the application context of the method user. Activity 2 involves the specification of value levers that are

important in determining the value of the smart service. In activity 3, these value levers are analyzed and quantified to finally add up the value potentials to obtain the total value potential of a specific smart service.

Our developed method contributes to the theoretical knowledge in three ways. First, existing academic research provides limited insights into how to systematically assess the value of smart services, which our developed method answers. Second, this paper provides a scientifically sound method that accounts for the different stakeholders' value co-creation (direct and indirect) and builds on the concept of smart products acting as boundary objects. Third, VAMOS lays the foundation for future research on the monetization and commercialization strategy of smart services by presenting a possible approach using customer and supplier value (besides the cost and competition perspective) as a dominant reference to develop a suitable revenue model for the respective smart service.

Keywords:

Smart Service; IoT; Value; Method; Design Science Research; Situational Method Engineering

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