Conceptualization of Digital Opportunities for Incumbents

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‘If opportunity doesn’t knock, build a door.’

(Milton Berle)

Für meine Familie, allen voran Christoph, Doris und Günther.

Spezieller Dank an meine Mentoren Max und Michael.

Abstract

Digital technologies are driving socio-technical change on an individual, organizational, and societal level. Examples include changes to the nature of products – an ever-increasing number of which are connected to the Internet of Things (IoT) – and the sharing of digital data across industry boundaries, enabling companies to deliver an increasingly diverse range of services and develop new business models. However, incumbents often struggle to identify and leverage digital opportunities – i.e., action possibilities leading to new products, services, or business models – and current literature fails to provide the necessary guidance. To address this need, the central question in this thesis relates to the identification and leveraging of digital opportunities for incumbents, in general, and digital opportunities enabled by the IoT, in particular. In addition, the thesis involves a method deep-dive on taxonomy design, a method that supports the understanding of novel phenomena such as digital opportunities.

In taking a generalized view of digital opportunities for incumbents, the thesis offers two conceptual perspectives that help to structure and clarify the solution space for identifying and leveraging such opportunities. Research article #1 presents a novel design theory comprising a taxonomy of digital opportunities for incumbents and related heuristic mechanisms for opportunity-led ideation. Building on and extending the resource-based view of the firm as justificatory knowledge, the thesis contributes to descriptive and prescriptive knowledge on digital innovation. Research article #2 complements this theory-focused approach by providing empirical evidence from an exploratory case study of an Australian utility provider, which proactively developed a strong opportunity focus despite operating in a low-competition and regulated environment. As a result, two facets of opportunity exploration are distinguished (i.e., core and new business opportunities) that require diverging capabilities.

This thesis goes on to present detailed perspectives on the structure and value of digital opportunities enabled by the IoT. Research article #3 proposes a taxonomy of business-to-thing (B2T) interaction patterns which accounts for smart things that transform the relationship a firm has with its products and customers. Drawing on weak and strong sociomateriality theory as justificatory knowledge, the B2T interaction patterns provide support to academics and practitioners making theory-led design decisions related to IoT-enabled opportunities. As the commercialization of IoT-solutions remains a critical barrier to market success, research article #4 develops and evaluates a model for assessing the customer value of IoT-solutions, which needs to be understood as a crucial pre-requisite for effective monetization. The model consists of a framework and corresponding value levers that support practical applicability, emphasizing the need to include both the frontstage and backstage value of processes and products and services. Research article #5 also takes an economic perspective, in this case with an internal focus, presenting a model that supports algorithm selection for predictive maintenance by full-service providers in industrial contexts.

Fast-changing environments require support for analysing and understanding novel phenomena, such as digital opportunities. Hence, this thesis concludes by contributing a close examination of taxonomy design, a method that aims at conceptualizing phenomena based on the classification of objects. After identifying and analysing taxonomy articles from leading IS journals, research article #6 finds that the taxonomy design process often lacks transparency and that taxonomies are hardly evaluated. To address these shortcomings, an outlook to the article's prescriptive extension is provided in the form of an extended taxonomy design process that specifically covers the evaluation phase and that is complemented by corresponding taxonomy design recommendations.

In summary, this thesis contributes a conceptualization of digital opportunities for incumbents relying on a broad portfolio of qualitative and quantitative research methods (i.e., taxonomies, explorative case study research, Design Science Research, and data analytics) and different forms of empirical evidence (i.e., primary and secondary data sources). Further, this thesis builds upon and extends relevant theory, such as the resource-based view of the firm, organizational ambidexterity, dynamic capabilities, and sociomateriality.

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I. Introduction[1]

New technologies provide novel opportunities. Fundamental examples include the invention of the wheel, which not only eased transportation (Dixit et al., 2017): The spinning wheel also revolutionized textile manufacturing and the water wheel transformed food production (Friedel, 2007). Much later and less obviously, the elevator brought profound changes to housing – and to the construction business – in modern nations. It seems hard to imagine, but before elevators enabled the development of skyscrapers and made penthouses popular, top floors merely functioned as attics, to be used for housing staff or as storage space. The arrival of elevators provided construction and housing companies with opportunities that would change the skylines of the world's major cities (Samsung C&T, 2018).

Although technological change has always been part of human life, today these changes are occurring at unprecedented speed and on an unprecedented scale, creating an opportunity-rich environment for society and business alike. Social media technologies – such as Instagram, for example – required less than six months to reach 50 million users, whereas radio took almost 40 years to achieve the same number (Gimpel et al., 2018). Ongoing digitalization affects all industries and requires companies to actively identify and leverage digital opportunities in order to sustain competitive advantage (Ciriello et al., 2018; Fang et al., 2018; Fichman et al., 2014). Today, however, two decades after digital technologies first unleashed the wave of digitalization, a sobering observation can be made: Many incumbents are still struggling or even failing to ride the digital wave. *Blockbuster*, *Kodak* and *Sears*, are just a few prominent examples of companies who have succumbed in the wake of change (Birkinshaw et al., 2016; Lucas and Goh, 2009; Wade, 2018), and the experience of incumbents in the digital economy is often compared to that of surfers caught between 'the fear of sharks and the thrill of big-wave surfing' (Dawson et al., 2016, p. 1).

Digitalization is described as the socio-technical phenomena driven by the emergence and adoption of digital technologies at an individual, organizational, and societal level (Berger et al., 2018; Legner et al., 2017). Although often used interchangeably, 'digitalization' should be distinguished from the term 'digitization' which is defined as 'the technical process of converting analogue signals into a digital form' (Legner et al., 2017, p. 301). Digital technologies involve the context-specific use of digital resources (e.g., IT infrastructure, sensors, actuators) to create, extract, analyze, and communicate information (Zuppo, 2012). Examples include relatively established technologies, such as Mobile and Cloud Computing, as well as emergent technologies, such as Social Media and the Internet of Things (IoT) (Gartner, 2018, 2015). Digital technologies have three characteristic aspects (Yoo et al., 2010): (1) *re-programmability*, as a device's operational logic is isolated

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

from its physical embodiment; (2) *data homogenization*, as analogue signals are converted into binary numbers for dynamic information storage, transmission and processing; and (3) *self-referential nature,* because digital technology is dependent on the use of digital technologies, which, in turn, has positive network effects. Such technologies can be classified and assessed according to four layers: the *device, network, contents*, and *service* layers (Benkler, 2006; Yoo et al., 2010). Building on these layers, Berger et al. (2018) propose seven archetypes of digital technologies grouped into three clusters, i.e., platform and connectivity technologies; actor-based products and sensor-based data collection technologies; analytical insight generation, analytical interaction, and augmented interaction technologies (Berger et al., 2018).

The digitalization of products, services, and business models is often understood as the third wave of IT-driven transformations. The first wave mainly involved the automation of individual activities (e.g., bill paying), while the second wave, influenced by the Internet, enabled the integration and coordination of individual activities across the supply chain (e.g., workflow management). These first two waves focused on internal productivity gains, and changes to the products themselves were minimal (Porter and Heppelmann, 2014). Today, however, the third wave of digitalization is not only changing the nature of products by equipping them with sensors, actuators, and connectivity. Digital data from these products can also be 'combined easily with other digital data to deliver diverse services, which dissolves product and industry boundaries' (Yoo et al., 2010, p. 726). As a result, digital technologies allow for novel opportunities at the customer interface, which incumbents must identify and leverage (Vial, 2019).

The question of how new opportunities can be identified and 'translated into digital innovation initiatives' (Kohli and Melville, 2018, p. 206) relates to the initiation phase of the digital innovation process. This initiation is followed by development, implementation, and exploitation phases (Kohli and Melville, 2018). Digital innovation relates to the creation of new products, services, or business models that result from the use of digital technology as either a means or an end. The outcomes are not necessarily digital (Ciriello et al., 2018; Nambisan et al., 2017; Vega and Chiasson, 2019). Specifically, the initiation phase of the digital innovation process requires a strong focus on opportunity and is critical to innovation success (Kohli and Melville, 2018).

Whereas the term 'opportunity' has been used and investigated by various research communities (e.g., innovation, strategic management, marketing), entrepreneurship research was most influential in defining the term (Ardichvili et al., 2003; Shane and Venkataraman, 2000). Key concepts differentiate between 'third-person' and 'first-person' opportunities and the 'discovery view' and the 'creation view'. Whereas a 'third-person' opportunity represents a generic opportunity, a 'first-person' opportunity relates to a specific actor hinging on its context and characteristics (McMullen and Shepherd, 2006). And whereas the 'discovery view' approaches opportunities as objective phenomena – analogous to mountains waiting to be discovered and climbed (Eckhardt and Shane, 2003; Shane and Venkataraman, 2000) – the 'creation view' assumes that opportunities are created rather than discovered. They refer to 'mountain building' rather than 'mountain climbing'. As a consequence, the materialization of the opportunity (i.e., the mountain) depends on the actions taken by the actor (e.g., piling up earth) (Alvarez et al., 2012; Alvarez and Barney, 2007). In this thesis, digital opportunities are defined as 'first-person possibilities for action enabled by digital technologies which may lead to the introduction of innovative products, services, or business models' (research article #3, p. 43).

Specifically, the IoT enables a new class of digital opportunities resulting from the 'increased feasibility of embedding digital sensors and processors in a wide range of everyday items and then connecting them up into an Internet of Things' (Fichman et al., 2014, p. 338). As a consequence, continuous connections between companies and their customers emerge, as contextual data about the condition and usage of smart products and services can now be accessed and leveraged (Siggelkow and Terwiesch, 2019). Typical examples include remote monitoring and proactive services, as offered by Oral B's connected toothbrush, Whirlpool's proactive replenishment of supplies, and Kaeser's Sigma Air operator model, which charges customers per cubic meter compressed air, rather than selling machines. Furthermore, smart products can be leveraged as platforms from which to offer or broker new services in two- or multi-sided markets (Stummer et al., 2018; Svahn et al., 2017). For example, LG connects a fridge to Amazon's Alexa for integrated grocery shopping, and Volvo leverages its customers' cars for new 'roam delivery' services. Accordingly, in a study involving over 50 organizations, Gimpel et al. (2018) found that smart products and services are understood to offer specifically relevant opportunities to enrich value propositions.

Research shows that a strong focus on opportunities drives growth more effectively than does an approach guided by necessity (Verheul and van Mil, 2011) and that innovation performance is positively correlated with financial performance (Cohen et al., 2019). At the same time, the digital innovation literature in the Information Systems (IS) discipline has been criticized for its lack of focus on opportunities, and the initiation phase of the digital innovation process remains 'understudied and poorly understood' (Kohli and Melville, 2018, p. 204). Unlike well-defined problem-response strategies (e.g., Lean Management), little is known about how opportunities can be identified and leveraged in an organizational context. Existing opportunity research, mainly conducted in the context of entrepreneurship, does not address incumbents, and their resource-rich environments are rarely acknowledged as potential strategic differentiators related to digital opportunities (Alvarez and Barney, 2013; Becker et al., 2015; Davidsson, 2016; Shane and Venkataraman, 2000). Therefore, the fundamental question of this thesis relates to the identification and leveraging of digital opportunities for incumbents (i.e., established organizations with a rich resource base).

This doctoral thesis is cumulative and consists of six research articles, which address the central research question by applying different conceptual and theoretical lenses, different forms of empirical evidence, qualitative and quantitative methods, and varying levels of granularity. In addition, a close investigation of taxonomy design – a method to support the understanding of novel phenomena such as digital opportunities – is provided. As a result, the research articles in this thesis are assigned to one of three topics, as outlined in Figure 1: *Identifying and Managing Digital Opportunities*, *Digital Opportunities Enabled by the Internet of Things*, and *Method Deep-dive: Taxonomy Design in IS*. Providing novel perspectives on digital opportunities for incumbents, this thesis is relevant for research scholars and practitioners alike.

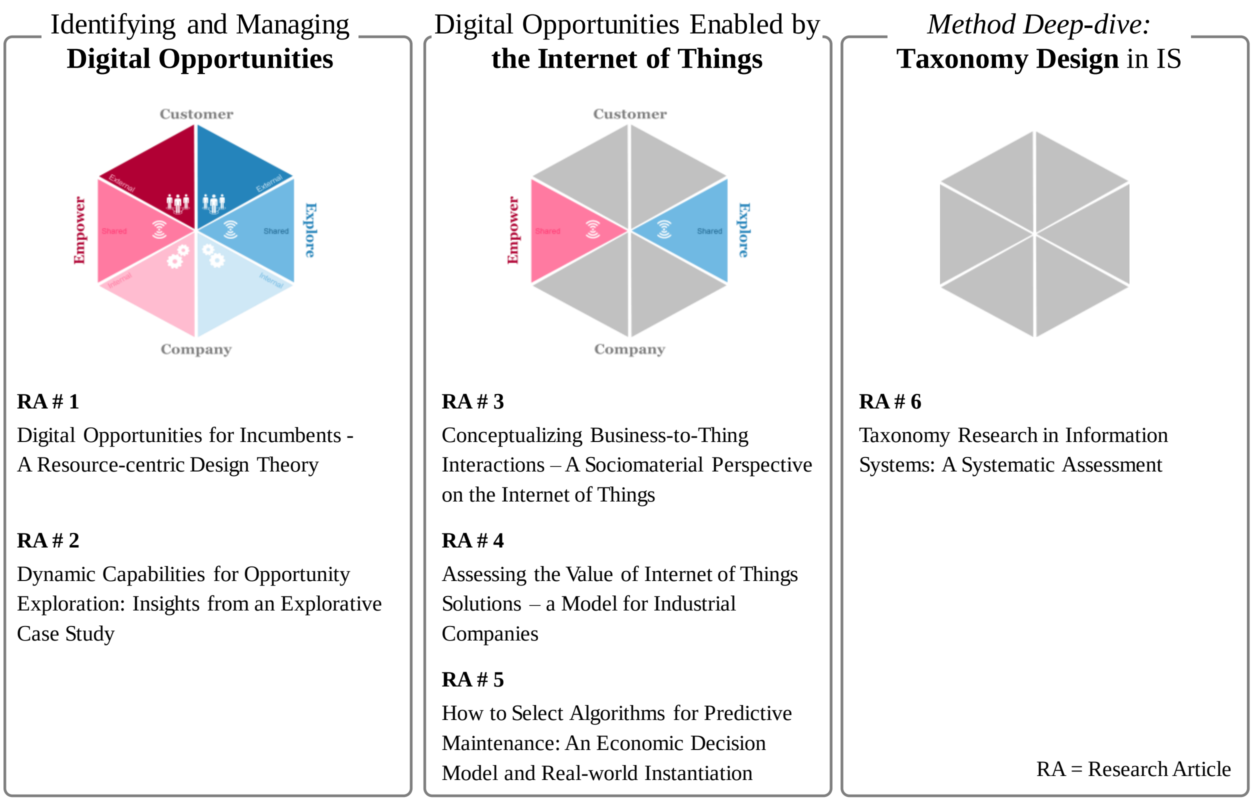


Figure 1 Assignment of the Research Articles to the Topics Structuring this Doctoral Thesis

As incumbents struggle to identify and leverage digital opportunities, and as the literature lacks corresponding theoretical understanding, this thesis firstly provides two conceptual perspectives on opportunities for incumbents (i.e., taxonomy and case-study based framework), which support the overarching identification of digital opportunities and conceptualize opportunity management practices (Section II.1 – including research articles #1 and #2). Thereby, article #1 details the overarching structure of the thesis, as exemplified by the hexagon in Figure 1. This hexagon illustrates six classes of digital opportunities for incumbents, with two of the six classes mainly enabled by the IoT (middle layer). Accordingly, this is followed by detailed perspectives on digital opportunities enabled by the IoT, such as a study presenting novel business-to-thing (B2T) interactions (Section II.1 – including research article #3). Further, to complement the predominantly technological and management-focused perspectives on IoT-solutions, two additional economic perspectives are provided: A model for assessing the customer value of IoT-solutions, which lays the ground for effective monetization, and an economic perspective on algorithm selection for predictive maintenance facilitated by Industrial IoT-solutions (Section II.2 – including research articles #4 and #5). This thesis ends with an overarching method contribution that builds on insights from the taxonomy development method applied in two of the research articles (#1 and #3) and identifies shortcomings from 33 taxonomy articles from leading IS journals that were investigated in detail. As an outlook to the article's prescriptive extension, an extended taxonomy design process is announced that addresses the identified shortcomings and that is complemented by corresponding taxonomy design recommendations (Section II.3 – including research article #6).

Section III concludes this doctoral thesis with an outlook on future research. Section IV comprises the publication bibliography, and Section V includes additional information on all research articles (V.1), my individual contributions (V.2), and the research articles themselves (V.3 - 8).

II. Overview and Research Context[2]

1 Identifying and Managing Digital Opportunities

Academics and practitioners agree that, in order to maintain a competitive advantage and thrive in the digital economy, incumbents need to focus on digital opportunities and leverage new forms of discovering innovative ideas (Ciriello et al., 2018; Fang et al., 2018; Fichman et al., 2014). However, incumbents, in particular, are in danger of stagnating and missing opportunities over time (Chandler, 1990). Kevin Sneader, global managing partner of McKinsey & Company, calls this a 'more sails approach' (Sneader, 2019a, p. 1) referring to the commercial sailing industry, which (unsuccessfully) tried to fight off steam technology by improving their sailing capabilities. In other words, rather than attempting to capitalize on their opportunity-rich environments, incumbents often tend to focus on becoming better at what they are already good at (Crittenden et al., 2019; Sneader, 2019a).

Although the construct 'opportunities' is considered relevant in research and practice, it remains vague and conceptually under-specified (Davidsson, 2015). For example, the initiation phase of the digital innovation process – which requires a strong focus on opportunity – lacks clarity, and practices with which to identify and seize opportunities in the organizational context are perceived as an empirically elusive 'black box' (Becker et al., 2015; Dimov, 2011; Kohli and Melville, 2018). Among the few studies addressing the initiation phase of the digital innovation process, scholars mainly focus on niche aspects such as the influence of organizational knowledge (Carlo et al., 2012; Mishra and Agarwal, 2010) or the relevance of digital technologies in idea generation (Oldham and Da Silva, 2015).

In contrast to the IS discipline, which has been criticized for its lack of focus on the initiation phase of digital innovation and opportunities (Kohli and Melville, 2018), opportunity research represents a core research focus in the entrepreneurship domain, with a focus on individual entrepreneurs and the individual-opportunity nexus (Alvarez and Barney, 2013; Becker et al., 2015; Davidsson, 2016; Shane and Venkataraman, 2000). Naturally, entrepreneurship research does not address incumbents, least of all when it comes to utilizing their existing resources as potential strategic differentiators. The few articles that address digital opportunities for incumbents lack theoretical foundation, for example, Bughin and van Zeebroeck's (2017a) types of digital strategies, and Weill and Woerner's (2018) framework for defining digital business models. Hence, it remains unclear how incumbents can leverage the resources at their disposal in order to identify digital opportunities, and the current literature fails to provide theory-guided and empirically validated opportunity management practices. To address this need, research articles #1 and #2 provide two conceptual perspectives on

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

opportunities for incumbents, which support the overarching identification of digital opportunities and structure opportunity management practices.

Research article #1 addresses Nambisan et al.'s (2017) question 'what theories can inform on the creation/discovery of such [digital] opportunities?' (p. 227) by developing and evaluating a *nascent design theory* in line with the Design Science Research (DSR) paradigm (Gregor, 2006; Gregor and Hevner, 2013; Hevner et al. 2004). Specifically, this nascent design theory comprises a taxonomy of digital opportunities (Figure 2) and related heuristic mechanisms for opportunity-led ideation (Figure 3).

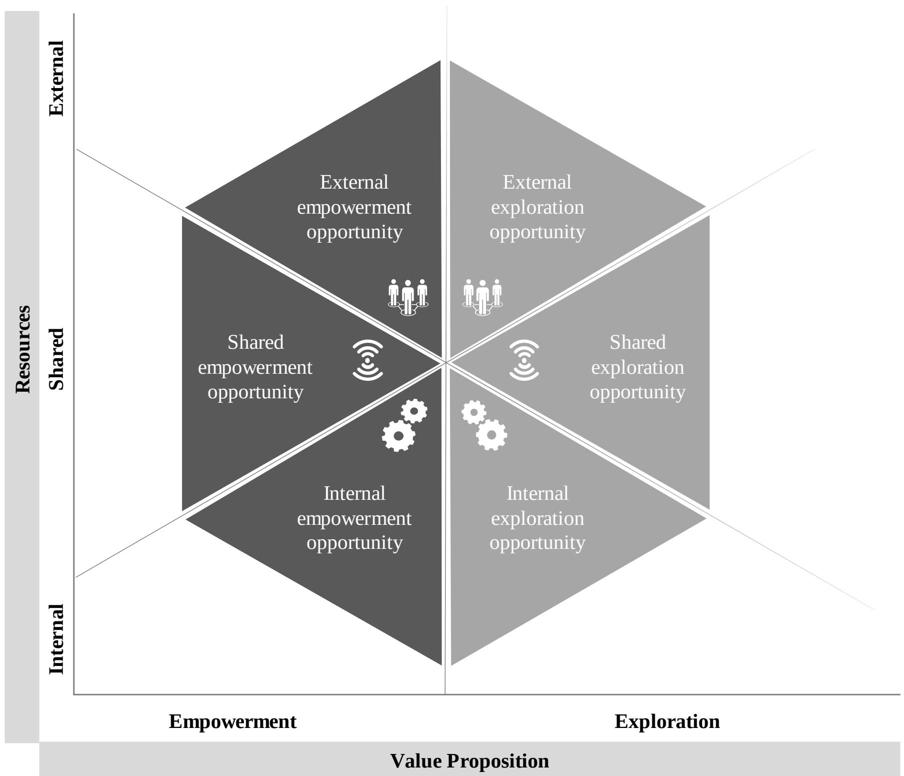


Figure 2 Taxonomy of Digital Opportunities: Opportunity Classes

The taxonomy distinguishes six digital opportunity classes building on two dimensions: (1) the incumbent's *value proposition* and (2) the *resources at the disposal of incumbents* in the digital economy. In the first dimension, the characteristics refer to the incumbent's *empowerment of existing value propositions* or their *exploration of new value propositions*. In the second dimension, the characteristics refer to the *internal, shared*, and *external* resources at the incumbent's disposal (for details refer to Table 1). Thereby, the taxonomy builds on and extends the resource-based view of the firm (RBV) as justificatory knowledge (Grant, 1991; Lavie, 2006; Priem, 2007), which is subject to change in the digital economy.

Table 1 Taxonomy of Digital Opportunities: Dimensions and Characteristics

Dimensions	Characteristics	Description
Value Proposition	Empowerment	▪ Digital opportunity focus is on *empowering* the existing value proposition (within traditional industry boundaries) ▪ *Examples:* Improvement of existing products, services, or business models by delivering value faster, cheaper, more comfortably, or more sustainably
	Exploration	▪ Digital opportunity focus is on *exploring* a new value proposition (within or beyond traditional industry boundaries) ▪ *Examples:* New products, services, or business models, perceived as new by the incumbent organization, not objectively new as measured by the lapse of time
Resources	Internal	▪ A company’s internal tangible and intangible assets, and operational and dynamic capabilities ▪ Through digital technologies, such as artificial intelligence, robotics, or distributed ledger, incumbents gain new abilities to understand, utilize, and control internal resources ▪ *Examples:* Property, patents, human capital, technology development, analytics abilities
	Shared	▪ A company’s physical or virtual boundary objects, including agency, which allow for a continuous connection with the customer ▪ Through digital technologies such as the IoT or digital channels, *shared resources* are owned and controlled by the customer while remaining remotely accessible and addressable by the company ▪ *Examples:* Connected car (physical), a digital bank account (virtual), or a personalized mobile app (virtual)
	External	▪ A company’s customers and related communities, including their assets and capabilities ▪ Through digital technologies such as platforms, *external resources* can be leveraged and proactively contribute to an incumbent's business model ▪ *Examples:* Customers taking over social media advertising or mutual customer service

In addition to the taxonomy of digital opportunities, 30 heuristic mechanisms (i.e., 5 per opportunity class) are provided. These serve as ‘cognitive shortcuts’ to opportunity-led ideation (Daly et al., 2012; Yilmaz et al., 2011). Both the taxonomy of digital opportunities and the heuristic mechanisms were evaluated via the classification of 150 real-world digital initiatives, an assessment of usefulness via the Q-sort method (Nahm et al., 2002; Oberländer et al., 2018), and via focus groups involving academics and practitioners (Gibson and Arnott, 2007). The overall contribution is a model with a prescriptive purpose targeted at incumbents, understood as a nascent design theory in line with Gregor (2006) and Gregor and Hevner (2013). This model contributes to the descriptive and prescriptive knowledge on digital innovation, providing novel perspectives on resources in the digital economy.

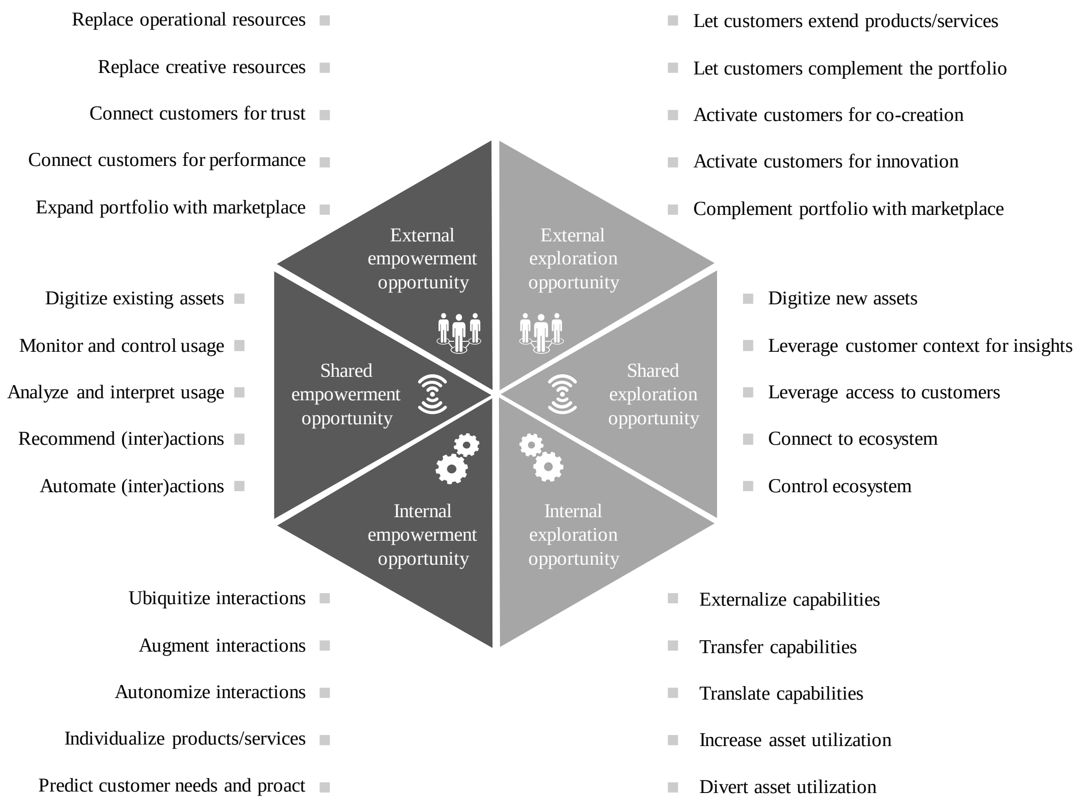


Figure 3 Heuristic Mechanisms for Opportunity-led Ideation

Complementing the theory-focused approach of research article #1, research article #2 provides insights on concrete opportunity management practices via an exploratory case study. *Queensland Urban Utilities* (QUU) is selected as a unique case, worth analyzing in depth (El Sawy and Bowles, 1997 Miles and Huberman, 1994). QUU is an Australian utility provider, which proactively changed into an ambidextrous organization with a strong opportunity focus despite operating in a low-competition, regulated public sector environment. Public sector organizations usually operate on a commercial basis providing various private goods and services for sale, are publicly owned, and are considered as 'self-financing commercial enterprises' (Lane, 2005, p.19). Exploratory case-study research was found to be appropriate in this context in order to examine and reflect QUU's opportunity management, which represented an emerging phenomenon and, therefore, required further investigation in a real-world context (Benbasat et al., 1987; Gephart, 2004; Yin, 2009).

The resulting findings provide a three-fold contribution: Firstly, a conceptual framework (Figure 4) to structure opportunity management practices is introduced, building upon organizational ambidexterity (OA) (March, 1991; Tushman and O'Reilly, 1996) and dynamic capabilities (DC) (Teece et al., 1997; Teece, 2007; Wade and Hulland, 2004) as theoretical lenses. Thereby, two types of opportunity exploration are found (i.e., core and new business opportunities) which require divergent sensing and seizing capabilities. Specifically, QUU adopted a dual opportunity focus, driven by regulatory boundaries and organizational characteristics. This focus distinguishes two types of opportunities, which either aim to enhance the core business (i.e., core business opportunities) or create new revenue streams (i.e., new business opportunities). Correspondingly, QUU assigned two distinct exploration teams responsible for sensing and seizing the two different types of opportunities.

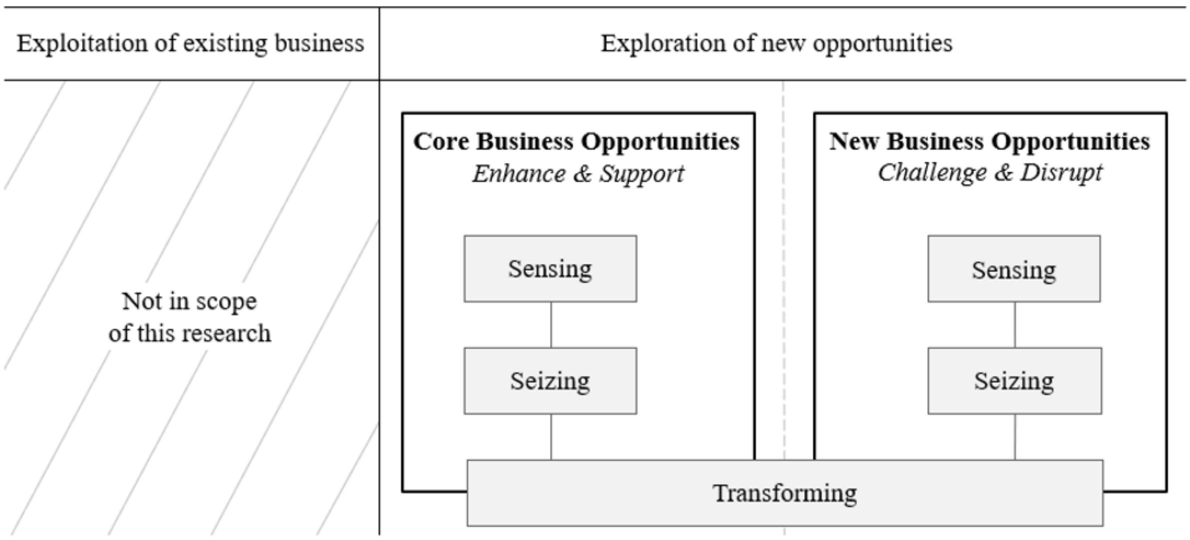


Figure 4 Conceptual Framework including Two Facets of Opportunity Exploration

Second, by building upon the conceptual framework, including two facets of opportunity exploration, 15 practice areas which span sensing, seizing, and transforming capabilities were inductively developed. These practice areas and their diverging foci for core and new business opportunities are highlighted in Figure 5. It is noteworthy that transforming capabilities relate to core and new business opportunities alike, as both types of opportunities demand overarching organizational transforming capabilities (e.g., transforming governance, culture, knowledge transfer). Third, for each practice area, corresponding actionable practices are determined, i.e., concrete management practices for operationalizing opportunity exploration. These actionable practices aim to detail the managerial understanding of opportunity exploration and support incumbents in developing concrete opportunity management practices (Harris et al., 2009).

Table 2 Overview of Opportunity Practice Areas and their Focus for Core and New Opportunities

	Core Business Opportunity Focus	Practice Area	New Business Opportunity Focus	
Sensing	Support business	Sensing Focus	Challenge business	Sensing
	All business units	Internal Opportunity Sources	Selected business units	
	Research-related	External Opportunity Sources	Market-related	
	Part-time owners	Opportunity Ownership	Full-time owners	
	Open access	Opportunity Exchange	Exclusive access	
Seizing	Within the business	Decision Makers	Ring-fenced from the business	Seizing
	Open discussion	Decision Process	Exclusive discussion	
	Multi-dimensional KPIs	Decision Criteria	Finance-related KPIs	
	Percentage of revenue	Funding	Expansionary budget	
	Open for all employees	Implementation Team	Hand-selected members	

	Practice Area	Opportunity Focus	
Transforming	Transforming Strategy	Opportunity focus	Transforming
	Governance	Decentralized structures	
	Transforming Culture	Visionary managers as role models	
	Transforming Exchange	Open discussions across hierarchy levels	
	Knowledge Transfer	Exchange among opportunity players	

In sum, research article #2 details the understanding of opportunity exploration capabilities and supports practitioners by providing actionable opportunity management practices. It is argued that these theoretical and practical contributions are relevant and transferable to both public and private sector organizations.

2 Digital Opportunities Enabled by the Internet of Things

The IoT integrates physical objects into the networked society. As the term has not been consistently defined, research article #3 proposes that the IoT should be understood as ‘the connectivity of physical objects equipped with sensors and actuators to the Internet via data communication technology’ (Oberländer et al, 2018, p. 488). This understanding builds on 16 different definitions available at the time. As one of the most disruptive current technologies, the IoT enables a new class of digital opportunities, turning physical objects from passive devices into smart things with their own agency. As a result, these smart things are able to act with increasing autonomy (Porter and Heppelmann 2015; Rosemann 2014; Yoo et al. 2012). Equipping products with sensors and actuators also establishes continuous connections to, and low-friction interactions between, companies and their customers, as remote emergency services in cars or the ubiquitous use of smart watches and smart speakers demonstrate (Beverungen et al., 2017; Porter and Heppelmann, 2014; Siggelkow and Terwiesch, 2019). Contextual data about the condition and usage of smart things can now be accessed and leveraged by companies. This not only enables the enhancement of existing products and services but also the development of new business models, such as product-as-a-service or product sharing (Porter and Heppelmann, 2015). In every case, the IoT holds huge economic potential. The global number of smart things is predicted to grow from less than 20 billion in 2016 to around 75 billion devices by 2025 (Columbus, 2016; statista, 2016). Reuters predicts an economic potential of up to USD one trillion per year following an annual growth rate of more than 20% (Reuters, 2019).

Smart things – which are IoT-equipped physical objects – represent the nucleus of the IoT, connecting the physical with the digital world (Borgia, 2014; Porter and Heppelmann, 2014). To clarify the transformative potential of smart things, Püschel et al. (2016) developed a multi-layer taxonomy grouping the characteristics of smart things into four layers and ten dimensions. The *thing layer, interaction layer*, *data layer,* and *service layer* thereby account for established IoT technology stacks, as proposed by Yoo et al. (2010) and Porter and Heppelmann (2015). At the *thing layer*, smart things are characterized by basic sensing capabilities (i.e., the ability to access object-related or environmental information) and acting capabilities (i.e., the ability to communicate or interact with the environment). The *interaction layer* describes the transition from the smart thing's physical representation to the digital layers, with interactions specified in terms of direction, multiplicity, and partners. The *data layer* distinguishes among data sources (e.g., internal status, context) and data usage (e.g., transactional, analytical). Finally, the *service layer* relates to a smart thing's offline functionality as well as its purpose, which specifies where and how the smart thing creates value for its users (e.g., additional digital services, integration into an ecosystem). Huber et al. (2020) build on this groundwork to develop a domain-specific modelling language to capture IoT-enabled smart service systems.

Since the introduction of the term IoT, when RFID technology was first presented at the Massachusetts Institute of Technology in 1999, research has focused on technological aspects and engineering challenges (Atzori et al., 2010; Kortuem et al., 2010). Complementing this technology-focused perspective, some of the more recent research attends to management-focused work in the business-to-business (B2B) and business-to-customer (B2C) contexts (Boos et al., 2013; Geerts and O'Leary, 2014; Porter and Heppelmann, 2015). In the B2C context, for example, Porter and Heppelmann (2014) and Rosemann (2014) were the first to provide high-level insights into IoT-related challenges and opportunities, highlighting new business models and an economy of shared things as emerging topics. After that, more specific IoT-related research questions were addressed by, for example, Balaji and Roy's (2017) study on the determinants of value co-creation for IoT-enabled retail technology, and Ayaz et al.'s (2019) conceptual trust model on behavioural factors affecting consumers' trust of the IoT. In the B2B context, research often relates to IoT-technology, termed the Industrial IoT (IIoT), which links the basic pillars of digital manufacturing by connecting industrial assets (e.g., machines, control systems) with IS and business processes (Sisinni et al., 2018). The resultant increases in the availability of data hold great potential which has been examined in multiple studies related, for example, to process optimization, quality control, and maintenance strategies (Al Aani et al., 2019; Chen et al., 2019; ur Rehman et al., 2019; vom Brocke et al., 2018).

While the individual contributions made by these studies are undisputable, this thesis addresses two research gaps related to digital opportunities enabled by the IoT. Firstly, research article #3 argues that current IoT research fails to provide a structured perspective on IoT-enabled interactions between smart things, customers, and businesses. To address this need, research article #3 presents a taxonomy of business-to-thing (B2T) interactions, which supports sense-making and the theory-led design of digital opportunities enabled by the IoT. Research articles #4 and #5 subsequently argue that current IoT research also fails to provide economic perspectives on the IoT even though these are a prerequisite for monetization or algorithm-selection. Therefore, research article #4 presents a model for assessing the customer value of IoT-solutions which lays the ground for effective (value-based) monetization, and research article #5 develops an economic perspective on algorithm selection for predictive maintenance as facilitated by Industrial IoT-solutions. All three articles lay the ground for the theory-led design of digital opportunities for incumbents, including the value assessment of selected IoT-solutions.

First, as smart things become increasingly autonomous actors capable of transforming 'the relationship a firm has with its products and with its customers' (Porter & Heppelmann, 2015, p. 98), research article #3 proposes a taxonomy of B2T interaction patterns. Following the iterative taxonomy development method provided by Nickerson et al. (2013), the resulting taxonomy draws on sociomateriality theory as justificatory knowledge for studying the interactions among the actors involved in B2T interactions (i.e. things, customers, and businesses). Following strong sociomateriality (Orlikowski, 2007; Orlikowski and Scott, 2008), the taxonomy of B2T interactions conceptualizes smart things, customers, and businesses as sociomaterial actors that are neither exclusively social nor material but enacted through sociomaterial practice. At the same time, accounting for weak sociomateriality (Jones, 2014; Leonardi, 2013), these actors are viewed as separate and stable entities with a social or material core. The actors can, therefore, engage in interactions that are defined by two actors 'given in advance that come together and engage in some kind of exchange' (Suchman, 2007, p. 267). On the one hand, the core of a business is classified as social in that its managers and staff are human. Likewise, customers and their communication devices (e.g., smartphones or computers) are seen as sociomaterial actors with a social core. On the other hand, as physical objects with embedded technology, smart things are conceptualized as socio-material actors with a material core.

Figure 5 illustrates interactions performed by sociomaterial actors as interaction patterns. Illustration 5a depicts a traditional B2C interaction between a business and a customer. For instance, a car, which is a thing (T), can be used by a customer (C) of a business (B) (e.g., a car manufacturer). As, traditionally, the car's ability to interact is limited, only the customer and the business can interact regarding topics such as maintenance. In contrast, the IoT enables the active participation of smart things. An example in the automotive context is Tesla's connected car, which automatically requests software updates (Porter & Heppelmann, 2014). The three actors and their sociomaterial entanglement are illustrated in Figure 5b, where actors with a social core are represented as circles and actors with a material core as boxes.

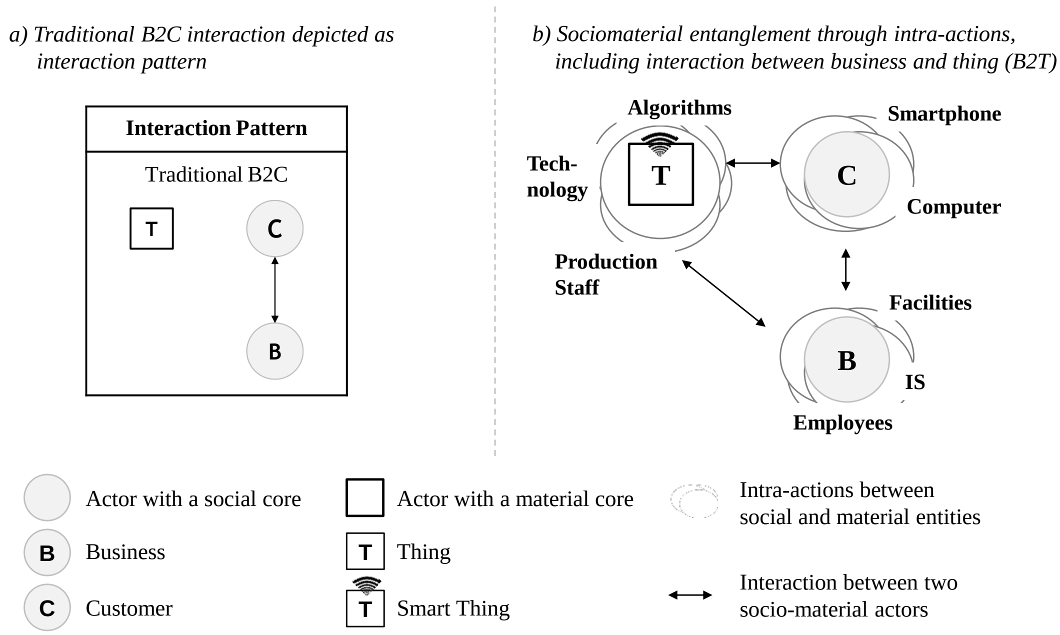
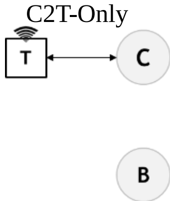
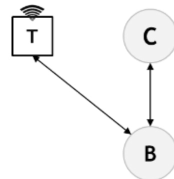
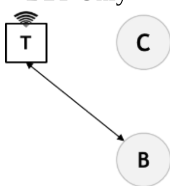
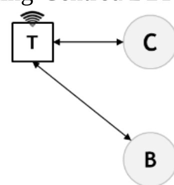
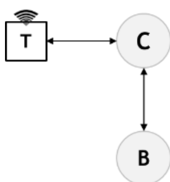
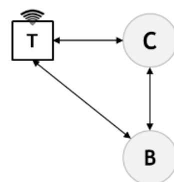
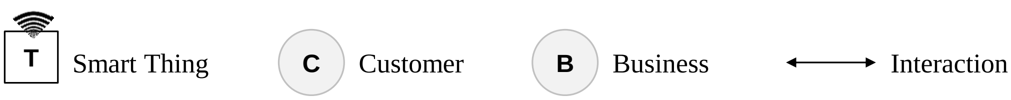


Figure 5 Interaction Pattern involving Sociomaterial Actors with a Social and a Material Core

In line with its meta-characteristic – which relates to *interactions between a smart thing, a business, and a customer as sociomaterial actors* – the taxonomy covers the following three dimensions: (1) interaction between a smart thing and a customer, (2) interaction between a smart thing and a business, and (3) interaction between a customer and a business. The mutually exclusive and exhaustive characteristics are 'yes' and 'no' for each dimension. The various combinations of dimensions and characteristics give rise to eight different patterns of interaction. We excluded one pattern which did not feature any interactions, and another which featured only interactions between a customer and a business (B2C) as neither of these patterns fell within the scope of this study. The six remaining B2T interaction patterns are illustrated in Table 3 wherein their key characteristics are noted.

Table 3 Taxonomy of Business-to-Thing (B2T) Interaction Patterns

Interaction Pattern	Characteristics	Interaction Pattern	Characteristics
C2T-Only 	▪ Interaction solely between a smart thing and a customer ▪ No interaction with a business	Business-Centred B2T 	▪ Business as the central party and gatekeeper ▪ No direct interaction between a smart thing and a customer
B2T-Only 	▪ Interaction solely between a smart thing and a business ▪ No direct interaction with a customer	Thing-Centred B2T 	▪ Smart thing as the central party and gatekeeper ▪ No direct interaction between a customer and a business
Customer-Centred B2T 	▪ Customer as the central party and gatekeeper ▪ No direct interaction between a smart thing and a business	All-In B2T 	▪ All three actors interact directly with each other



We evaluated the taxonomy by using it to classify simple, real-life IoT-solutions (i.e., involving not more than one T, one C, one B) and by assessing its reliability and validity using the Q-sort method. We also used the taxonomy to analyze complex IoT-solutions, such as *Nest*, *RelayRides*, and *Uber*. This demonstrated that B2T interaction patterns can be composed and combined with traditional interactions (e.g. B2C and B2B) and other IoT-enabled interactions such as customer-to-customer (C2C) and thing-to-thing (T2T) interactions. To demonstrate how the B2T interaction patterns support the analysis of complex, real-life IoT-solutions, the example of *Nest* is depicted in Figure 6, which builds on a *Thing-Centred B2T* interaction pattern, multiple *T2T interactions*, and a *B2B interaction.*

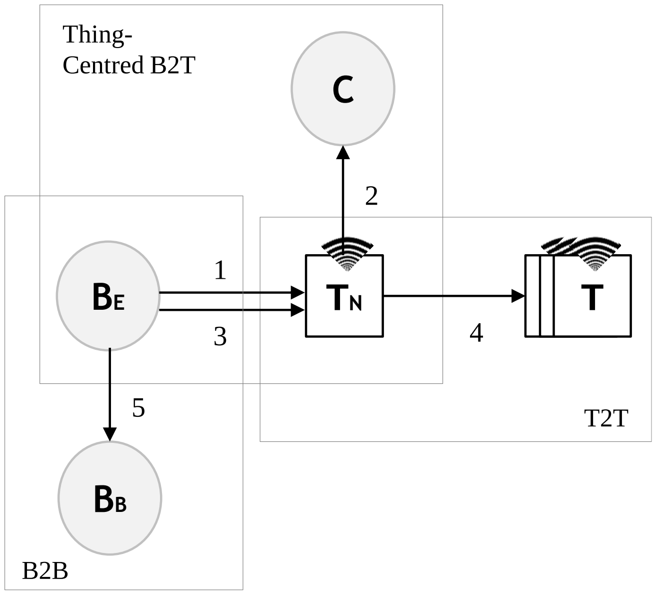


Figure 6 Analysis of Nest's ‘Rush Hour Rewards’ applying the Taxonomy of B2T Interactions

The steps involved in the *Nest* example are as follows:

(1) The energy provider (B_E) notifies the Nest thermostat (T_N) of the anticipated peak hours (i.e., rush hours) for the following day.

(2) The Nest thermostat informs the customer (C) of the anticipated peak hours for the following day. The customer can cancel the rush hour service if desired.

(3) If the customer accepts the rush hour service, the energy provider reduces and adjusts the thermostat’s activities during these rush hours.

(4) The thermostat requests that other energy-intensive smart things (T, e.g. ‘Whirlpool’ washing machine, ‘Charge Point’ charging devices) postpone or adjust their consumption.

(5) The amount of energy saved is recorded and rewarded monetarily. Corresponding payments are processed via a bank (B_B), based on information previously provided by the customer.

In sum, this analysis demonstrates how the proposed B2T interaction patterns introduce a novel catalytic idea that helps structure the design space enabled by the IoT. Further, the patterns aim to support academics and practitioners making design decisions related to IoT-enabled services and business models. Thus, the taxonomy of B2T interaction patterns provides a foundation for sense-making and theory-led design of digital opportunities enabled by the IoT.

Whereas the taxonomy of B2T interaction patterns supports the analysis and design of IoT-enabled interactions, commercialization, in general, and effective monetization, in particular, remain critical barriers to market success (Bilgeri and Wortmann, 2017; Fantana et al., 2013). Despite the significant economic potential, the actual revenues generated from IoT-solutions remain below predicted levels (Gartner, 2014; Odusote et al., 2016) and a recent benchmarking study highlights that two-thirds of the participating companies were unable to generate significant revenues from the use of smart services, even though more than 70% of these companies had invested in such services (Friedli et al., 2019).

The challenges of monetizing IoT-solutions stem from constitutive characteristics that differ from those of traditional products. This is particularly the case in the industrial context. IoT-solutions are associated with high and recurrent development costs but near-zero costs for replication, distribution, and individual use (Fichman et al., 2014). Furthermore, value creation via IoT-solutions relies on a combination of physical products and digital services involving multiple stakeholders generating various direct and indirect benefits (Del Giudice, 2016; Sheth, 2016). The traditional cost-plus-pricing (i.e., production costs plus margin) which industrial companies usually apply disregards monetization potential as the actual value generated for the customer – and for associated stakeholders – is neglected. Therefore, IoT-solutions demand a different monetization logic: one which accounts for the constitutive characteristics of such solutions, not only as physical products but also as digital services. Research article #4 thus argues that IoT-solutions demand value-based monetization, which, in turn, requires a sound conceptual understanding of the customer value generated by IoT-solutions (Kindström, 2010).

Among extant work on the monetization of IoT-solutions, Wortmann et al. (2017) provide a high-level overview of revenue models, Lee and Lee (2015) develop a real-options approach for the value assessment of IoT investments, and Fähnle et al. (2018) consider the internal value generated in the case of an industrial company. Although the IS community has a notable track-record in examining the business value of IT (Kohli and Grover, 2008; Melville et al., 2004; Otim et al., 2012; Sun et al., 2016), a structured perspective on the value creation IoT-solutions is missing. Against this backdrop, research article #4 develops and evaluates a model that consists of a framework for assessing the value of IoT-solutions and of corresponding value levers that support practical applicability. Figure 7 illustrates the framework for assessing the value of IoT-solutions, including an overview of the value categories which need to be considered for the respective stakeholders. The framework considers three stakeholders in an archetypical B2B2C value chain: the business supplier (BS) serving the business customer (BC) who serves the (end-) consumer (C). Even though the study focuses on the industrial context, the scope is purposely extended towards the C to capture all of the value categories that directly or indirectly contribute to the BC's value perspective. This setup is intentionally generic and can easily be extended, e.g., by incorporating additional BCs and their Cs.

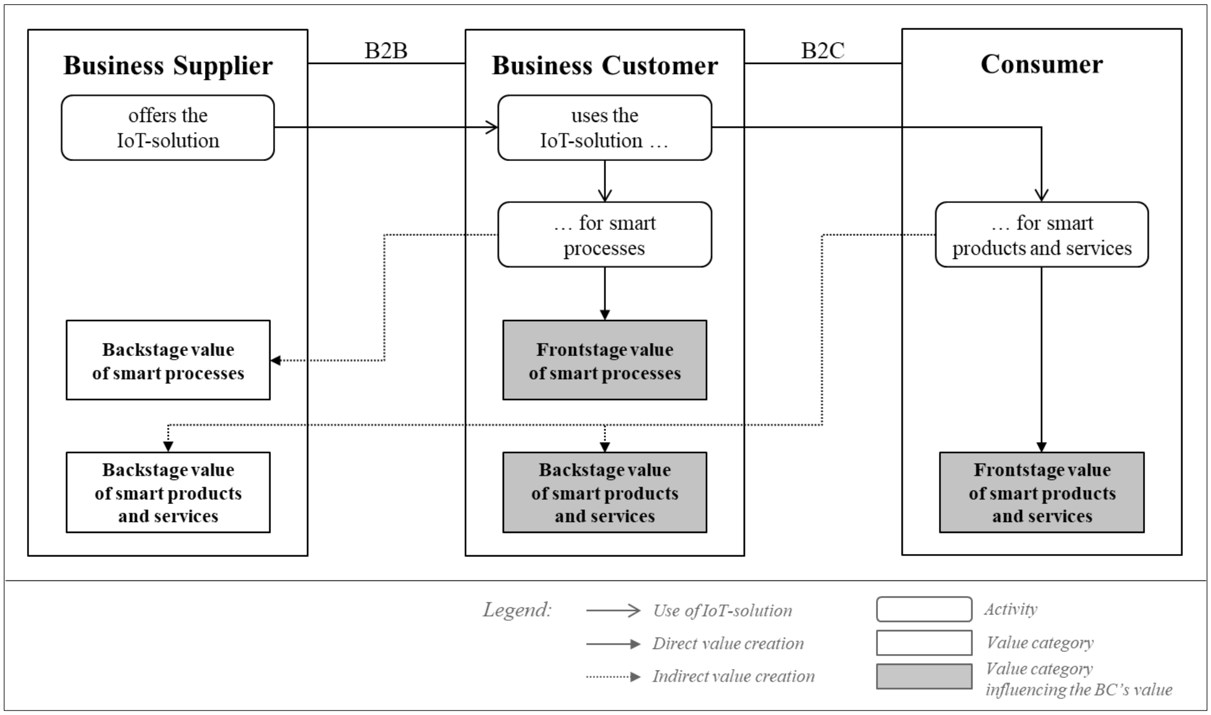


Figure 7 Framework for assessing the customer value of IoT-solutions

The framework emphasizes the need to include the *frontstage* as well as *backstage value* of *processes*, and *products and services* building upon relevant work on the IoT as justificatory knowledge (Fleisch et al., 2015; Nicolescu et al., 2018; Oberländer et al., 2018). The differentiation of frontstage and backstage value relates to Beverungen et al.'s (2017) conceptualization of smart things as boundary-spanning objects which enable dual value creation. The user, on the one hand, benefits from the frontstage usage of the product by creating and capturing value-in-use, e.g., through monitoring, optimization, remote control, and autonomous adaption. The provider, on the other hand, benefits from backstage analytics such as remote monitoring and diagnostics, data aggregation, data analytics, or decision-making (Beverungen et al., 2017). Thus, the solution provider can generate future value by developing new and improved offerings based on continuous customer connections and knowledge drawn from backstage analytics (Siggelkow and Terwiesch, 2019). This, in turn, positively affects the value of future processes or products and services.

For a first operationalization and to support practical applicability, the article further investigates how IoT-solutions affect the customer value in the framework's value categories by providing concrete value levers derived from a structured literature review. Specifically, three value lever trees are presented which can be used to determine the C's and BC's frontstage value and the BC's backstage value. Thereby, the primary goals were to guide practitioners in assessing the value of IoT-solutions, to prove the applicability of the framework, to classify specific value levers which feature in the literature, and to reflect on corresponding state-of-the-art literature. The model was evaluated using a two-fold, real-world approach in which it was discussed in five interviews with representatives from industrial companies and applied in order to quantify the value of two real-world IoT-solutions. As a model with a prescriptive purpose, research article #4 contributes to the prescriptive knowledge of the IoT and supports practitioners in assessing IoT value potential for effective monetization.

Whereas research article #4 provides a model focusing on the customer value of IoT-solutions, research article #5 focuses on the company value of predictive maintenance facilitated by IIoT-solutions. Driven by the availability of data and computing capacity, the IIoT has enabled the development of new maintenance strategies that represent one of the largest cost-drivers in the production context (Windmark et al., 2018). Traditionally, maintenance strategies are either reactive or preventive, mostly relying on experience paired with basic information on maintenance cycles and machine characteristics (Bevilacqua and Braglia, 2000; Swanson, 2001). In contrast, data-based predictive maintenance (PdM) leverages available system data to analyze system or process fluctuations and provide automatic alarms if threshold values are exceeded (Bevilacqua and Braglia, 2000).

Multiple studies from the academic and practical literature have proven that PdM is more advantageous than preventive or reactive maintenance (Gu et al., 2017a; Gu et al., 2017b; Xu et al., 2015; Zarte et al., 2017). Gu et al. (2017b), for instance, demonstrate significant economic benefits in the automotive industry. Various qualitative and quantitative approaches to the implementation of PdM are available, such as expert systems, statistical methods, and neural networks (Baptista et al., 2018; Li et al., 2014; Venkatasubramanian et al., 2003). For the selection and evaluation of PdM algorithms, hitherto, absolute and relative prediction errors are considered, as for example the work of Baptista et al. (2018) shows. However, Li et al. (2014) were the first to note that an algorithm's prediction errors impact costs (e.g., travel or repair costs) and that, therefore, economic factors should be taken into account for algorithm selection. In more detail, the two types of prediction errors (i.e., alpha errors, ignoring system failures, and beta errors, falsely indicating system failures) are negatively correlated, cannot be jointly optimized, and are associated with different costs. Adjusting a given algorithm in order to decrease the number of alpha errors will increase the number of beta errors, as reducing ignored failures implies an increased likelihood of false alarms. From a statistical perspective, this trade-off cannot be unambiguously solved, and cost implications are neglected. Thus, algorithm selection from a purely statistical perspective may not necessarily lead to the most advantageous economic outcome. Along these lines, research article #5 argues that a holistic economic perspective on PdM algorithm selection is missing, especially in the context of full-service providers, where the maintenance supplier bears all of the costs and risks of maintenance.

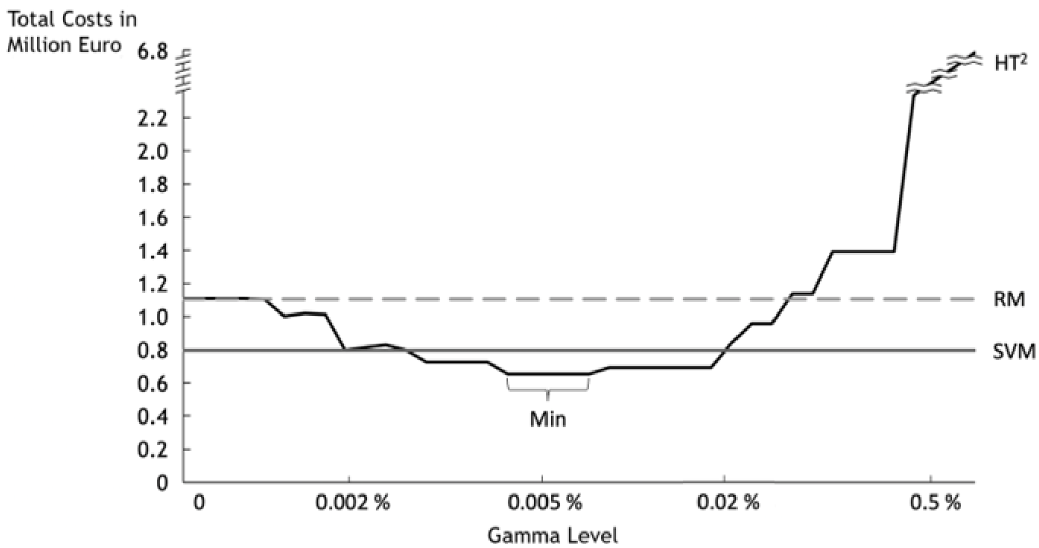
In order to address this need, research article #5 presents a decision model, developed using the Design Science Research paradigm, which enables industrial full-service providers to take an economic perspective to the selection of predictive maintenance algorithms. Building on three design objectives, research article #5 outlines the foundation of the decision model in the form of four decision model states. These include the actual system (e.g., machine) states (no failure or failure) and two types of algorithm predictions (alarm, no alarm). The four possible model states are translated into cost implications (Table 4), reflecting the economic impact of the prediction-based actions, such as the cost of the service technicians' travel, checks, and repairs to the system, as well as penalties in the case of missed service levels. The decision model compares the algorithm´s prediction with the actual state of the system at a given point in time in order to determine the model states and to translate them into cost implications.

Table 4 Cost implications of four PdM model states based on the observation matrix x

Actual system state / Algorithm prediction	**No Failure**	**Failure**
Alarm	*False negative (beta error):* Travel Costs (TC) + Check Costs (CC)	*True positive:* Travel Costs (TC) + Check Costs (CC) + Repair Costs (RC)
No Alarm	*True negative:* No Costs	*False positive (alpha error):* Travel Costs (TC) + Check Costs (CC) + Repair Costs (RC) + Penalty Costs (PC)

Applying an economic perspective to the selection of a pre-defined set of PdM algorithms first requires that, for each algorithm, the setup (e.g., regarding error sensitivity) with the minimum total costs for the historic time period in question is selected, balancing the trade-off between alpha error and beta error cost implications. Finally, the total costs for each of the individual algorithms are compared and the algorithm with the overall minimum total costs is to be selected. For an overview of the formulas that detail the decision model, please refer to the full paper in Appendix V.7.

In line with the DSR paradigm, the decision model was instantiated and evaluated in a real-world setting (Sonnenberg and vom Brocke, 2012), where the case-company was a European machinery company providing full-service solutions in the field of car wash systems. Harnessing historic sensor data from 4.9 million car washes, the instantiation demonstrated the applicability and effectiveness of the decision model, which was used to compare the cost implications of exemplary PdM algorithms, i.e., among others Support Vector Machine (SVM) and Hotelling T2 Control Chart (HT²). Figure 8 shows the results in terms of costs compared to reactive maintenance (RM) as a lower boundary. It is important to note that HT² provides access to internal structural knowledge and that, therefore, the prediction error sensitivity of the algorithm can be adjusted via the gamma level (balancing alpha and beta errors). By contrast, SVM is a 'black-box' approach that does not allow for the adjustment of prediction error sensitivities (hence, remaining flat).



HT[2] **=** Hotelling T2 Control Chart **RM =** Reactive Maintenance **SVM =** Support Vector Machine

Figure 8 Comparison of PdM algorithm cost implications instantiating the decision model

In sum, the instantiation led to significant cost savings (i.e., more than 40% compared to RM in the case under consideration) and, thus, demonstrated the effectiveness of the decision model. This effectiveness was confirmed by the case company, which is working towards the permanent inclusion of the decision model and is also keen to apply the model to other types of failures and systems.

3 Method Deep-dive: Taxonomy Design in Information Systems

Categorization, Parson and Wand inform us, 'is a fundamental skill learned in childhood' (Parsons and Wand, 2008, p. 1040). As the previous sections have illustrated, digital technologies are changing today's world at unprecedented speed and scale (Berger et al., 2018; Legner et al., 2017). One result is an ever-increasing number of novel phenomena for categorization. Examples of such phenomena include digital opportunities, in general, (research article #1) and B2T interactions (research article #3), in particular. The IS domain, linking 'the natural world, the social world, and the artificial world of human constructions' (Gregor, 2006, p. 613), plays a key role in emergent understandings of socio-technical change. In this context, taxonomies represent an important tool for understanding and analyzing complex phenomena based on the classification of objects (Nickerson et al., 2013). Two of this thesis' six research articles (#1 and #3) present taxonomies with which to structure and conceptualize novel technology-driven phenomena (i.e., digital opportunities for incumbents, B2T interactions), which were developed using Nickerson et al.'s (2013) taxonomy development method.

In the IS domain, Nickerson et al. (2013) were the first (and, to the best of our knowledge, the only) authors to propose a structured and replicable taxonomy development method. Combining inductive and deductive approaches, Nickerson et al.'s (2013) method draws on taxonomy methods from related disciplines, e.g., Doty and Glick (1994) and Bailey (1994). Since its publication in the *European Conference on IS proceedings* and the *European Journal of Information Systems (EJIS),* Nickerson et al.'s (2009, 2013) work has been cited more than 300 times, indicating substantial diffusion and impact. Nickerson et al.'s taxonomy development method comprises seven steps, which should be followed in an iterative manner. It starts with the determination of a meta-characteristic, which is derived from the purpose and target users of the taxonomy. Secondly, the researchers determine objective and subjective ending conditions which signal the termination of the iterative development method. Thirdly, the researchers decide on the approach for the first/next iteration: In an empirical-to-conceptual (i.e., inductive) iteration, a subset of objects is drawn, specific characteristics that differentiate the objects are derived, and related characteristics are grouped into dimensions. In a conceptual-to-empirical (i.e., deductive) approach, new characteristics (and dimensions) are, conceptualized before researchers examine objects for these characteristics and dimensions. The result, after each iteration, is a (revised) taxonomy that is examined by the researchers for the ending conditions. The taxonomy development process continues with the next iteration until all ending conditions have been met (Step 7).

After reviewing 33 taxonomy articles published between 2013 and 2018 in leading Information Systems journals, research article #6 finds that – more than six years after the publication of Nickerson et al.'s (2013) method – the taxonomy design process still often remains opaque, that taxonomies are rarely evaluated, and that there is little guidance on how to evaluate them (Lösser et al., 2019; Szopinski et al., 2019). As these findings indicate a need for augmenting existing methodological guidance, the article's authors (together with fellow taxonomy researchers) are currently finalizing an extension of research article #6 that provides additional prescriptive guidance. This extension will be submitted early 2020 presenting an extended taxonomy design process (ETDP) complemented by actionable taxonomy design recommendations. It positions taxonomies as Design Science Research artefacts and integrates taxonomy design into the widely accepted Design Science Research methodology. It is noteworthy, that the extension of research article #6 does not want to substitute or discredit Nickerson et al.'s (2013) valuable work, but much more complement existing methodological guidance. Particularly, the recommendations are understood as useful, but optional support that further detail the steps of the extended method and that provide a listing of useful insights that might improve the taxonomy design process. In sum, the aim is to contribute to the prescriptive knowledge on taxonomy design by refining and extending the existing knowledge base for better building and evaluating taxonomies.

III. Conclusion

1 Summary

Digital technologies continue to provide novel opportunities for society and business alike. Two decades after digital technologies unleashed the first wave of digitalization, incumbents, in particular, are still struggling to effectively identify and leverage digital opportunities in order to sustain competitive advantage. Addressing the need to more comprehensively study the initiation phase of the digital innovation process (Kohli and Melville, 2018) – which requires a strong focus on opportunities – this doctoral thesis provides novel perspectives on digital opportunities for incumbents. Firstly, the thesis comes in response to the third wave of digitalization, which is not only changing the nature of products but also creating an unprecedented opportunity-rich environment across industry boundaries (Yoo et al., 2010). Secondly, this thesis examines specific opportunities enabled by the IoT that establishes continuous connections between companies and their customers (Siggelkow and Terwiesch, 2019). Thirdly, this thesis recognizes that tools for understanding and conceptualizing are gaining importance, driven by rapidly-evolving phenomena such as digital opportunities and the IoT. Therefore, this thesis ends with a systematic assessment of state-of-the-art taxonomy research in IS and an outlook to further prescriptive guidance.

On the topic of *Identifying and Managing Digital Opportunities*, section II.1 provides two conceptual perspectives on opportunities for incumbents, which help to structure and clarify the solution space for researchers and practitioners attempting to identify and manage opportunities. Research article #1 investigates how incumbents can identify digital opportunities grounded on the resources at their disposal. As a result, a nascent design theory is developed, involving a taxonomy of digital opportunities for incumbents and related heuristic mechanisms for opportunity-led ideation. Building on and extending the RBV as justificatory knowledge (Grant, 1991; Lavie, 2006; Priem, 2007), the taxonomy distinguishes six digital opportunity classes that allow for the classification of digital opportunities as a prerequisite to the development of sound scientific method (McKelvey, 1978; Posey et al., 2013). While the taxonomy adds to the descriptive knowledge on digital innovation, providing new perspectives on resources in the digital economy, the heuristic mechanisms add to the prescriptive knowledge, serving as 'cognitive shortcuts' to opportunity-led ideation (Daly et al., 2012; Yilmaz et al., 2011). Research article #2 complements the theory-focused approach of research article #1 by providing insights on concrete opportunity management practices using an exploratory case study. The case in question is that of QUU, an Australian utility provider, which proactively evolved into an ambidextrous organization with a strong opportunity focus, despite operating in a low-competition and regulated environment. Building upon OA (March, 1991; Tushman and O'Reilly, 1996) and DC (Teece et al., 1997; Teece, 2007; Wade and Hulland, 2004) as theoretical lenses, two types of opportunity exploration are distinguished (i.e., core and new business opportunities), which require divergent sensing and seizing capabilities. In addition, practice areas within the sensing, seizing, and transforming capabilities are presented, together with actionable opportunity management practices that are relevant and transferable to organizations in both regulated and non-regulated contexts.

On the topic of *Digital Opportunities enabled by the Internet of Things,* section II.2 presents more detailed perspectives on IoT-enabled opportunities such as novel B2T interactions. It also presents economic perspectives on the value assessment of IoT solutions and PdM algorithm selection. Research article #3 conceptualizes IoT-enabled interactions between smart things, customers, and businesses, drawing from weak and strong sociomateriality theory as justificatory knowledge (Orlikowski, 2007; Orlikowski and Scott, 2008). The resulting taxonomy of B2T interactions contains six B2T interaction patterns that introduce a novel catalytic idea for structuring the design space enabled by the IoT. Furthermore, the patterns aim to support academics and practitioners making design decisions related to IoT-enabled services and business models, providing a foundation for sense-making and theory-led design (Gregor & Hevner, 2013). Research paper #4 takes an economic perspective on IoT-solutions, addressing the challenge of commercialization, in general, and effective monetization, in particular (Bilgeri and Wortmann, 2017; Fantana et al., 2013). Against this backdrop, research article #4 develops and evaluates a model for assessing the customer value of IoT-solutions, which needs to be understood as a crucial pre-requisite for effective monetization. The model consists of a framework and corresponding value levers building on an exemplary and extendable value chain (B2B2C) in the industrial context. The framework emphasizes the need to include both frontstage and backstage value of processes as well as products and services, and draws on relevant work on the IoT as justificatory knowledge (Fleisch et al., 2015; Nicolescu et al., 2018; Oberländer et al., 2018). Research article #5 also contributes an economic perspective, yet, in this case, with an internal focus on the question of how industrial full-service providers can select PdM algorithms from an economic perspective. In response, research article #5 presents a decision model that translates the two types of algorithm prediction errors (i.e., alpha errors, ignoring system failures, and beta errors, falsely indicating system failures) into an economic calculus. As opposed to purely statistical perspectives, this allows for unambiguous and economically advantageous algorithm selection, which has proved beneficial in a real-world instantiation of the model.

On the topic of *Taxonomy Design in IS*, section II.3 adds a close methodological examination of taxonomies, as tools to facilitate understanding gain importance in today's fast-changing environment. Building on the analysis of 33 taxonomy articles from leading IS journals, research article #6 finds that the taxonomy design process often remains opaque, that taxonomies are rarely evaluated, and that there is little guidance on how to evaluate them (Lösser et al., 2019; Szopinski et al., 2019). As this indicates a need for augmenting existing methodological guidance, an outlook towards the article's prescriptive extension in the form of the ETDP and corresponding taxonomy design recommendations is provided.

2 Limitations and Future Research

As with any research endeavour, the results of this thesis are subject to some limitations. The following section focuses on an aggregated overview of these limitations and highlights themes for further research advancing the knowledge of digital opportunities for incumbents. Further detailed perspectives on the limitations can be found in the individual articles (see Appendix).

First, both conceptual perspectives on opportunities for incumbents (i.e., the taxonomy of digital opportunities and the case-study based framework of opportunity exploration) build on current digital innovation literature in IS (Ciriello et al., 2018; Nambisan et al., 2017; Vega and Chiasson, 2019), current opportunity definitions (Alvarez et al., 2012; Alvarez and Barney, 2007; Davidsson, 2015), and theoretical concepts (e.g., OA, DC, RBV), which serve as justificatory knowledge with which to understand and structure opportunities. However, as Davidsson (2015) notes, the opportunity construct is still elusive and not consistently defined (Davidsson, 2015). Furthermore, the digital innovation literature in IS has been criticized for a lack of focus on the initiation phase, wherein opportunities are relevant (Kohli and Melville, 2018). To address this gap, further research should attempt to develop a unified theory of digital innovation by complementing and integrating existing digital innovation knowledge. Such a unified theory should not only consolidate, describe, and structure digital innovation constructs across research disciplines, but also theorize relationships to relevant theoretical foundations such as organizational ambidexterity (March, 1991; Tushman and O'Reilly, 1996), dynamic capabilities (Teece et al., 1997; Teece, 2007), and the resource-based view (Grant, 1991; Priem, 2007).

Second, as this thesis does not provide any explanations or hypotheses for the relationship between specific actor characteristics and the selection or implementation of opportunities, future research should investigate variables that determine whether, and to what extent, particular opportunities are feasible, viable, or desirable for particular company types – for example, depending on their business design and organizational structure (Ross et al., 2019), the digital innovation process (Barros Teixeira et al., 2019), leadership (Bughin et al., 2019), or trust elements (Ayaz et al., 2019; Rosemann, 2019). There is also room for additional compare-contrast case studies to investigate relevant success and failure factors in real-world settings.

Third, the IoT not only enables novel opportunities but also increases sociomaterial entanglements (Orlikowski, 2007; Orlikowski and Scott, 2008) by equipping things with independent agency and turning them into autonomous interaction partners. This becomes particularly interesting if smart things are understood as ‘make-to-evolve’ artifacts that are not stable entities across time but evolve in the hands of customers. Examples include self-learning virtual assistants and self-configurable cars that autonomously adapt to their user’s needs. However, this thesis does not further examine how, or to what extent, the IoT enables and requires a new perspective on material agency that considers smart things as independent and, potentially, evolving actors. Therefore, future research should pay particular attention to the integration of strong and weak sociomateriality, the evolution of material agency driven by the IoT, and the implications of ever-evolving artifacts in the hand of customers.

Fourth, this thesis positions taxonomies as DSR artifacts (i.e., namely models) and provides an outlook to an integrated design process that guides taxonomy development under the DSR paradigm. The extended taxonomy design process provides various points of entry for revising a taxonomy. This underlines the iterative nature of taxonomies and supports the advancement of taxonomies after initial publication. However, the thesis does not provide any specific guidance on when and how to configure the extended taxonomy design process to meet specific research needs. Hence, future research should examine potential avenues for method configurations depending on the taxonomy's purpose, characteristics of the research project under consideration, or philosophical assumptions (e.g., positivist or interpretivist context).

In sum, the ability to identify, leverage, and conceptualize digital opportunities will gain further importance as 'the pace of change will never be this slow again' (Sneader, 2019b, p.1). It is my hope that this thesis supports researchers and practitioners by providing novel perspectives on digital opportunities for successfully riding the wave of digitalization.

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V. Appendix

1 Index of Research Articles

Research Article #1: Digital Opportunities for Incumbents – A Resource-Centric Design Theory

Oberländer A.M., Röglinger M., & Rosemann M. Digital Opportunities for Incumbents – A Resource-Centric Design Theory. *Submitted working paper.*

Research Article #2: Dynamic Capabilities for Opportunity Exploration: Insights from an Explorative Case Study

Baumbach S., Oberländer A.M., Röglinger M., & Rosemann M. (2020). Dynamic Capabilities for Opportunity Exploration: Insights from an Explorative Case Study. In *International Journal of Entrepreneurial Venturing* (in press).

Research Article #3: Conceptualizing Business-to-Thing Interactions – A Sociomaterial Perspective on the Internet of Things

Oberländer A.M., Röglinger M., Rosemann M., & Kees A. (2018). Conceptualizing Business-to-Thing Interactions – A Sociomaterial Perspective on the Internet of Things. In *European Journal of Information* Systems 27(4): 486-502. Earlier version published in *Proceedings of the 23rd European Conference on Information Systems (ECIS), Münster, Germany*.

Research Article #4: Assessing the Value of Internet of Things Solutions – a Model for Industrial Companies

Baltuttis D., Häckel B., Oberländer A.M., Seyfried J., & Röglinger M. Assessing the Value of Internet of Things Solutions – a Model for Industrial Companies. *Submitted working paper*.

Research Article #5: How to Select Algorithms for Predictive Maintenance: An Economic Decision Model and Real-world Instantiation

Fabri L., Häckel B., Keller R., & Oberländer A.M. How to Select Algorithms for Predictive Maintenance: An Economic Decision Model and Real-world Instantiation. *Submitted working paper.* Earlier version published in *Proceedings of the 27rd European Conference on Information Systems (ECIS), Stockholm and Uppsala, Sweden.*

Research Article #6: Taxonomy Research in Information Systems: A Systematic Assessment

Lösser B., Oberländer A.M., & Rau D. (2019). Taxonomy Research in Information Systems: A Systematic Assessment. In *Proceedings of the 27rd European Conference on Information Systems (ECIS), Stockholm and Uppsala, Sweden.*

2 Individual Contribution to the Research Articles

This thesis is cumulative consisting of six research articles that comprise the main body of work. All articles were developed in teams with multiple authors. Thus, this section is to detail the respective research settings and highlight my individual contributions to each research article.

Research article #1 (Oberländer et al.) was developed with two co-authors, whereas I was the leading author responsible for the model development and evaluation. Specifically, I designed the research method, identified the real-life objects for developing the taxonomy and heuristic mechanisms, and related our work to justificatory knowledge. Further, I organized, prepared, and performed the evaluations (i.e., Q-sort and focus groups). Although the research article represents, to a large extent, my work, the two co-authors were involved in each part of the project and helped to discuss and advance our contribution.

Research article #2 (Baumbach et al., 2020) was developed in a team of four authors. While two of the four co-authors collected the case study data on-site in Brisbane, Australia, all co-authors jointly developed the theoretical lens as the guiding structure of the analysis and elaborated the content together. I was particularly involved in the method design, the data coding, interpretation, as well as framework development. I also took a key role in revising the article for re-submission. Throughout, I was involved in each part of the project.

Research article #3 (Oberländer et al., 2018) was developed in a team of four authors, where all authors jointly developed the key concept of B2T interaction patterns. A former version of the article was presented at the 23rd European Conference on Information Systems (ECIS), Münster, Germany, after which we incorporated corresponding feedback to significantly advance our work. Thereby, I took a key role in the taxonomy development and application, the identification of real-world objects, the conduction of the Q-sort method for evaluation, as well as the underlying literature work. In sum, one co-author and I were leading (equally contributing) authors, whereas the two remaining co-authors were still involved in each part of the project.

Research article #4 (Baltuttis et al.) was developed in a team of five authors. All co-authors jointly developed the article's basic concept and created the content. Together with one of the co-authors, I was responsible for developing the conceptual framework as well as evaluating our model with the five industrial companies. Overall, the authors made equal contributions to the content of the research article and I was involved in each part of the project.

Research article #5 (Fabri et al.) was developed in a team of four authors. After a former version of the article was presented at the 27rd European Conference on Information Systems (ECIS), Stockholm and Uppsala, Sweden, one former co-author left the team and another co-author joined instead. All co-authors developed and refined the decision model together accounting for the feedback they received from the conference. I was particularly involved in the formal development of the decision model as well as the instantiation and evaluation with the case company.

Research article #6 (Lösser et al., 2019) was developed in a team of three authors who presented the article at the 27rd European Conference on Information Systems (ECIS), Stockholm and Uppsala. I was responsible for the coding and analysis of a sample of current taxonomy articles and deriving stimulating questions for further research. After the ECIS presentation, the authors joined forces with another research team that presented a research article on taxonomy evaluation to jointly develop prescriptive methodological guidance. Thereby, all seven co-authors jointly developed the key contributions, i.e., the extended taxonomy design process and recommendations, whereas I took a key role in deriving design recommendations for the building part and in conducting interviews to evaluate and refine our work. The resulting extension of research article #6 is currently being finalized and will be submitted early 2020.

3 Research Article #1: Digital Opportunities for Incumbents – A Resource-centric Design Theory

Authors: Oberländer A.M., Röglinger M., & Rosemann M.

Submitted working paper.

Extended Abstract

Digitalization presents companies with novel opportunities, i.e., action possibilities leading to new products, services, or business models. However, specifically incumbents struggle to identify digital opportunities, and current literature lacks guidance on how incumbents can leverage and re-purpose the resources at their disposal in the digital economy. Against this backdrop, our research question is as follows: *How can incumbents identify digital opportunities grounded on the resources at their disposal?*

Our response to this question – and our primary contribution – is a composed artifact that consists of a taxonomy of digital opportunities and related heuristic mechanisms for opportunity-led ideation. To build and evaluate this composed artifact, we adopted the Design Science Research paradigm (Gregor and Hevner, 2013). The taxonomy distinguishes six digital opportunity classes that involve the leveraging of extended resources in the customer context combined with and accessed through digital technologies. Specifically, the taxonomy includes two dimensions: (1) the incumbent's value proposition characterized by the opportunity to empower existing value propositions or to explore new value propositions and (2) the resources at the disposal of incumbents in the digital economy, referring to internal resources, shared resources (i.e., physical or virtual boundary objects that connect companies and customers) and external resources (i.e., company's customers and related communities). Thereby, the taxonomy builds on and extends the resource-based view of the firm (Barney, 1991; Grant, 1991) and current theoretical advancements as justificatory knowledge (Priem, 2007).

For each opportunity class included in the taxonomy, we developed heuristic mechanisms to provide incumbents with operational guidance for opportunity-led ideation. These heuristic mechanisms serve as 'cognitive shortcuts' (Daly et al., 2012) that support the derivation of specific digital action possibilities as potential instantiations of the taxonomy's opportunity classes. Thus, the mechanisms comply with the structure of the taxonomy and build on the same empirical foundation. They do not intend to replace creativity. Rather, they stimulate ways of thinking which expand the search space, structure the solution space, and allow for more effective ideation.

The taxonomy and the heuristic mechanisms were evaluated empirically, first, via the classification of 150 real-world digital initiatives implemented by incumbents and, second, by investigating their usefulness for the intended purpose and intended users. As for the latter, we used the Q-sort method and conducted three focus

groups, which in sum involved 29 academics and representatives from diverse incumbents. Accounting for the participants' inexperience with the taxonomy and the heuristic mechanisms, the evaluation results confirmed that the taxonomy and heuristic mechanisms are valid, reliable, and useful for practitioners and IS academics investigating digital opportunities for incumbents.

Overall, our artifact is a model with a prescriptive purpose targeted at incumbents, which we understand as nascent design theory in line with Gregor and Hevner (2013). It contributes to the descriptive and prescriptive knowledge on digital innovation, providing new perspectives on resources in the digital economy.

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4 Research Article #2: Dynamic Capabilities for Opportunity Exploration: Insights from an Explorative Case Study

Authors: Baumbach S., Oberländer A.M., Röglinger M., & Rosemann M.

Published in: *International Journal of Entrepreneurial Venturing* (in press).

Abstract: Digital technologies offer organizations new opportunities. However, unlike well-defined problem-response strategies (e.g., Lean Management), it remains elusive how to identify and leverage opportunities, particularly for public sector organizations. As extant knowledge lacks corresponding theory-guided and empirically validated opportunity management practices, this study provides insights on opportunity management practices through an exploratory case study. The case of interest is Queensland Urban Utilities, a utility provider which developed a strong focus on opportunity exploration despite operating in a low-competition environment. Building upon organizational ambidexterity and dynamic capabilities as theoretical lenses, we present a conceptual framework which distinguishes two opportunity types, namely core and new business opportunities. Along this framework, we present 15 practice areas and actionable practices, supported by real-life examples. Thereby, we identify two facets of exploration demanding divergent capabilities to sense and seize opportunities. Our study contributes to the understanding of exploration capabilities and supports practitioners in developing opportunity management practices.

Keywords: Opportunity; Opportunity Management; Organizational Ambidexterity; Opportunity Exploration; Dynamic Capabilities; Case Study Research; Single Case Study

5 Research Article #3: Conceptualizing Business-to-Thing Interactions – A Sociomaterial Perspective on the Internet of Things

Authors: Oberländer A.M., Röglinger M., Rosemann M., & Kees A.

Published in: *European Journal of Information Systems*, 2018, 27(4), 486-502.
Earlier version published in *Proceedings of the 23rd European Conference on Information Systems (ECIS), Münster, Germany*.

Abstract: The Internet of Things (IoT) is recognized as one of the most disruptive technologies in the market as it integrates physical objects into the networked society. As such, the IoT also trans-forms established business-to-customer interactions. Remote patient monitoring, predictive maintenance, and automatic car repair are examples of evolving business-to-thing (B2T) inter-actions. However, the IoT is hardly covered by theoretical investigations. To complement the predominant technical and engineering focus of IoT research, we developed and evaluated a taxonomy of B2T interaction patterns. Thereby, we built on sociomateriality as justificatory knowledge. We demonstrated the taxonomy's applicability and usefulness based on simple and complex real-life objects (i.e. Nest, RelayRides, and Uber). Our taxonomy contributes to the descriptive knowledge on the IoT as it enables the classification of B2T interactions and facilitates sense-making as well as theory-led design. When combining weak and strong socio-materiality, we found that the IoT enables and requires a new perspective on material agency by considering smart things as independent actors.

Keywords: Business-to-Thing; B2T; Internet of Things; Sociomateriality; Interaction Patterns; Taxonomy

6 Research Article #4: Assessing the Value of Internet of Things Solutions – a Model for Industrial Companies

Authors: Baltuttis D., Häckel B., Oberländer A.M., Seyfried J., & Röglinger M.

Submitted working paper.

Extended Abstract

The Internet of Things (IoT) is one of the most disruptive technologies associated with great value potential. However, actual revenues from IoT-solutions remain below expectations and effective monetization is considered a barrier to market success. Due to high development costs, low costs of replication, and value creation across stakeholders, IoT-solutions require value-based monetization rather than traditional 'cost-plus pricing'. As the current literature lacks corresponding guidance, we ask the following research question: *How to assess the customer value of IoT-solutions from the perspective of an industrial company?*

In response to this question, we developed a model composed of a framework for assessing the value of IoT-solutions as well as of corresponding value levers that support practical applicability. Thereby, we followed the Design Science Research paradigm (Gregor and Hevner, 2013) along three steps, i.e., the deductive framework development, the inductive derivation of value levers, and the real-world demonstration and evaluation, where we demonstrated and discussed our framework in five interviews with different companies from the field of industrial manufacturing. To evaluate general applicability and usefulness, we selected two real-world IoT-solutions from two industrial companies for an in-depth examination of the relevant value levers and an initial quantification of value potentials as pre-requisite for effective monetization.

Our framework shows an exemplary value chain with three relevant stakeholders, i.e., the business supplier (BS), the business customer (BC), and the (end-)consumer (C). The BS provides the IoT-solution to the BC who uses the IoT-solution either for improving his internal processes or for enhancing the products and services provided to the C. Building (among others) upon the work of Beverungen et al. (2017) as justificatory knowledge, we understand IoT-enabled devices as boundary objects enabling dual value co-creation, i.e., on the sides of the service user and the service provider. The frontstage value captures benefits which the user (i.e., the BC or C) experiences directly when using the IoT-solution. The backstage value captures benefits which cannot be exploited directly, but which indirectly benefit the solution provider (i.e., BS or BC), e.g., through data collection. Focusing on value levers that influence the BC's value, we accordingly identified three relevant value categories that need to be considered as pre-requisite for effective monetization (by the BS), namely (1) the frontstage value of smart processes for the BC, (2) the frontstage value of smart products and services for the C, as well as (3) the backstage value of smart products and services for the BC.

In addition, we inductively investigated how IoT-solutions affect the customer value along the conceptualized value categories presenting corresponding value levers for two reasons: On the one hand, we wanted to examine whether our framework could be effectively applied to classify specific value levers from literature. On the other hand, we aimed for an initial operationalization of our framework to support its applicability in practice. As a result, we incorporated the identified and consolidated value levers into a tree-like structure, however, without claiming exhaustiveness. The initial list of value levers needs to be carefully investigated, adjusted according to the objectives of use, and potentially updated.

In summary, from a theoretical viewpoint, our work contributes to the prescriptive knowledge of the IoT. From a practical viewpoint, we provide practical support for the effective monetization and value-based pricing of IoT-solutions targeting industrial companies.

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7 Research Article #5: How to Select Algorithms for Predictive Maintenance: An Economic Decision Model and Real-world Instantiation

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

Submitted working paper. Earlier version published in *Proceedings of the 27rd European Conference on Information Systems (ECIS), Stockholm and Uppsala, Sweden.*

Extended Abstract

Driven by the increases in data availability and computing power, Artificial Intelligence enables the transformation of the economy and society in new ways. In the industrial context, predictive maintenance (PdM) represents a promising application, and various Artificial Intelligence-based algorithms are available for implementation. Until now, the selection and evaluation of PdM algorithms have relied on statistical measures such as absolute and relative prediction errors. However, the algorithm selection according to purely statistical measures may not necessarily lead to the optimal economic results, as the two types of prediction errors (i.e., alpha errors, ignoring system failures and beta errors, falsely indicating system failures) are negatively correlated and cannot be jointly optimized. In addition, they are associated with different costs. As current literature fails to provide corresponding guidance in the industrial context and as academics and practitioners – in particular full-service providers – lack support when introducing PdM as a means to leverage the potential of AI, our research question is: *How to select PdM algorithms from an economic perspective in an industrial full-service provider context?*

To answer this question, we built and evaluated a holistic economic decision model for PdM algorithm selection from the perspective of industrial full-service providers adopting the Design Science Research paradigm (Gregor and Hevner, 2013) including three design objectives. To ensure that the decision model meets the design objectives and to account for the underlying mechanics of algorithm-based prediction, we first elaborated on the underlying statistical perspective, including the classification of alpha and beta prediction errors. As a result, the decision model compares the algorithm´s prediction (i.e., alarm, no alarm) with the actual state of a system (i.e., failure, no failure) at a given point in time in order to determine the model states and to translate them into cost implications. Subsequently, the associated cost implications are compared in order to select the economically advantageous algorithm.

To demonstrate the decision model’s applicability, effectiveness, and fidelity to real-world phenomenon, we instantiated the model in a real-world setting. The case company that we collaborated with is a European machinery provider that builds and operates car wash systems. The case company currently employs a preventive maintenance strategy complemented by reactive maintenance. In order to identify an economically

advantageous algorithm for PdM, we analysed sensor data from 4.9 million car wash cycles, which was provided by the case company. Together with the case company, we identified relevant failures of car wash systems within the data set. After data preparation, we trained, calibrated, and evaluated three types of algorithms (i.e., Artificial Neural Network, Support Vector Machine, Hotelling T^2 Control Chart) guided by the data analytics guidelines of Müller et al. (2016).

Applying our decision model, we compared the total costs of the three algorithms under consideration and selected the algorithm with the minimum total costs, thus validating the applicability and effectiveness of the decision model. Thereby, we demonstrated that our decision model enables users to focus on economic concerns in the process of algorithm selection, and to consider the cost implications of different error types. In summary, our work contributes to the prescriptive knowledge of Artificial Intelligence and algorithm selection, in general, and PdM, in particular, providing an economic perspective to a field that is otherwise a largely technical and computer science-oriented.

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8 Research Article #6: Taxonomy Research in Information Systems: A Systematic Assessment

Authors: Lösser B., Oberländer A.M., & Rau D.

Published in: *Proceedings of the 27rd European Conference on Information Systems (ECIS), Stockholm and Uppsala, Sweden.*

Abstract: Today's world is changing at unprecedent speed and scale becoming more complex to understand. Taxonomies represent an important tool for understanding and analyzing complex domains based on the classification of objects. In the Information Systems (IS) domain, Nickerson et al. (2013) were the first to propose a taxonomy development method, addressing the observation that many taxonomies have been developed in an 'ad-hoc' approach. More than five years after Nickerson et al.'s (2013) publication, we examined to what extent recently published taxonomy articles account for existing methodological guidance. Therefore, we identified and reviewed 33 taxonomy articles published between 2013 and 2018 in leading Information Systems journals. Our results were sobering: We found few taxonomy articles that followed any specific development method. Although most articles correctly understood taxonomies as conceptually or empirically derived groupings of dimensions and characteristics, our study revealed that the development process often remained opaque and that taxonomies were hardly evaluated. We discuss these findings and potential root causes related to method design, method adoption, and the general positioning of taxonomy research in the IS domain. Our study proposes stimulating questions for future research and contributes to the IS community's progress towards methodologically well-founded taxonomies.

Keywords: Taxonomy; Typology; Method; Literature Review