Novel Perspectives on Digital Transformation and IT Innovation Management

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Index of Research Papers

This doctoral thesis contains the following research papers:

Research paper P1: Berger S, Bitzer M, Häckel B, Voit C (2020) Approaching Digital Transformation – Developing a multi-dimensional Maturity Model.

In: *Proceedings of the* 28*th European Conference on Information Systems (ECIS), 2020 (VHB-JOURQUAL 3: category B)*

https://aisel.aisnet.org/ecis2020_rp/181/

Research paper P2: Bürger O, Häckel B, Voit C (2019) Toward an Economically Optimal Team Design in IT-related Innovation Projects.

Major Revisions in: *International Journal of Innovation and Technology Management (VHB-JOURQUAL 3: category C)*

Research paper P3: Voit C (2020) Science Drives Practice – or Vice Versa? Technology Hype Development Analysis Based on Scientific and Industrial Research.

Submitted to: *International Journal of Innovation and Sustainable Development (VHB-JOURQUAL 3: category C)*

Research paper P4: Häckel B, Pfosser S, Stirnweiß D, Voit C (2018) Determining Optimal Strategies for Investments in an Emerging IT Innovation.

In: *Proceedings of the 26th European Conference on Information Systems (ECIS), Portsmouth, UK, 2018 (VHB-JOURQUAL 3: category B)*

https://aisel.aisnet.org/ecis2018_rp/200/

Research paper P5: Geißler A, Häckel B, Übelhör J, Voit C (2019) Structuring the Anticipated Benefits of the Fourth Industrial Revolution.

In: *Proceedings of the 25th Americas Conference on Information Systems (AMCIS), Cancún, Mexico, 2019 (VHB-JOURQUAL 3: category D)*

https://aisel.aisnet.org/amcis2019/strategic_uses_it/strategic_uses_it/7/

Research paper P6: Häckel B, Übelhör J, Voit C (2020) Creating Competitive Advantage in E-Business Value Chains by Using Excess Capacity via IT-enabled Marketplaces.

Appears in: *ACM SIGMIS – The Data Base for Advances in Information Systems, 2020 (VHB-JOURQUAL 3: category B)*

I Introduction[1]

Digital transformation is primarily driven by the on-going and ever-faster emergence of digital technologies such as the internet of things, artificial intelligence, or cloud computing (Gimpel et al. 2018). In nowadays dynamic business environments, these technologies enable organizations to create novel business models (Iansiti and Lakhani 2017; Ross et al. 2017), and the thoughtful adoption of these technologies is essential to sustain competitiveness and profitability (Patrakosol and Olson 2007). Moreover, the pervasive digitalization and ever shorter innovation cycles force organizations of all industries to master the transformative impact of digital technologies and undergo a process of organizational change (Kohli and Melville 2018; Lucas et al. 2013). In this regard, digital transformation can be defined as the “socio-technical transformation that affects organizational structures, strategies, information technology (IT) architectures, methods, and business models” (Legner et al. 2017 p. 303) driven by digital technologies (Hess et al. 2016). To face up to this endeavor, organizations need to develop digital capabilities, adapt their traditional business model, develop new services, and engage in digitized value networks and adapt digital technologies. Furthermore, organizations must transform themselves as a whole, i.e., their organizational structures, processes, work approaches, and culture (Gimpel et al. 2018).

The fact that many organizations have recognized the need to address this topic is reflected by the worldwide investments in digital transformation activities across all industries. In 2019, these investments increased to a new high of $1.2 trillion, a rise of 18% over 2018 (IDC 2019). However, experts estimate that 70% of all digital transformation projects do not deliver the desired outcome (Libert et al. 2016; Tabrizi et al. 2019), as most organizational leaders struggle to understand the holistic impact of digital transformation (Berghaus and Back 2017). To support organizations in their digital transformation, prior research examined various approaches for the development of digital transformation strategies (Matt et al. 2015; Hess et al. 2016; Chanias 2017) or derived action fields (Gimpel et al. 2018; Gimpel and Röglinger 2017), success factors (Holotiuk and Beimborn 2017) and challenges (Piccinini et al. 2015; Heavin and Power 2018) that organizations need to consider during their digital transformation.

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[1] Since it is in the nature of a cumulative doctoral thesis that consists of individual research papers, this Section, the beginning of Chapters II to IV as well as the last Chapter V partly comprise content taken from the research papers included in this thesis. To improve the readability of the text, I omit the standard labeling of these citations.

Thereby, digital transformation poses strategic challenges for both incumbents and “digital-born” organizations in all industries. Apart from industries already closely related to digital technologies, like online retailing or financial services, especially the manufacturing sector is subject to a dynamic digital transformation that entails massive changes driven by technologies like cyber-physical systems or internet of things (Urbach and Röglinger 2019; Govindarajan and Immelt 2019). Digital transformation offers new challenges and opportunities as manufacturing organizations need to develop from traditional manufacturers of physical products to providers of individual service solutions (Govindarajan and Immelt 2019; Lerch and Gotsch 2014) and from product-centered to customer-oriented organizations in order to stay competitive (Buschmeyer et al. 2016). The $1.2 trillion investments in digital transformation activities across all industries in 2019, as mentioned above, are headed by the manufacturing sector with $222 billion (IDC 2019) and reflect the awareness for this topic. However, also other industries fierce a massive transformation in the context of digitalization. For example, in the healthcare sector, technologies enhance the efficiency of healthcare delivery and make medicine more personalized and precise. Traditional financial services providers are developing new artificial intelligence- or blockchain-based services to meet changing customer demands and to counteract competitive pressure from financial technology start-ups – so-called FinTechs (Mackenzie 2015). Apart from that, IT-enabled marketplaces are forming new ecosystems and allow organizations from almost all industries to outsource whole business processes, in particular standardized IT-driven processes, to external providers that allocate all technical, personnel, and other resources (Sengupta et al. 2006).

These examples demonstrate how technologies and innovations drive whole industries. Still, many organizations, especially long-established incumbents, are struggling or even failing to master this endeavor. Apparently, the fact that 88% of the Fortune 500 companies that existed in 1955 have disappeared cannot be explained by unsuccessful digital transformation strategies alone. However, more recent downfalls of incumbents such as Kodak, Blockbuster, or Toys R Us demonstrate that organizations need to continually innovate to survive in changing business environments (Birkinshaw et al. 2016; Lucas and Goh 2009). Therefore, more important than individual technologies, organizations need to understand the opportunities provided by technologies, how these opportunities can change their business model and environment and how to translate them into innovation initiatives (Kohli and Melville 2018). Thus, technologies on their own do not provide a real competitive advantage – but the technology-enabled innovations, which are aligned to the customer and the business environment. Consequently, digital transformation requires the adoption of technologies. However, adaptation requires not only a deep understanding of certain technology peculiarities, but also the derivation of IT innovations and holistic integration into the organization’s processes, culture, and business model.

Thereby, the two terms digital technologies and IT innovations are closely related. IT innovations can be defined as the organizational application of IT (Swanson 1994, p. 1072) and usage of digital technologies for new outcomes. In particular, IT innovations relate to new, possibly trendsetting, products, services, processes, or business models that differ qualitatively from existing ones and result from the use of technologies (Abrahamson 2009). IT innovations, especially in the form of products and services, can be new for an organization (Davila et al. 2012), the customer (Wang and Ahmed 2004), or a market segment (Kim et al. 2005). IT Innovations in the form of processes are mainly used to develop new methods and procedures for intra- and inter-organizational processes (Wang and Ahmed 2004). Business model innovations primarily change the way a company creates value for its customers (Davila et al. 2012). The examples mentioned above, as well as the close link between digital transformation, technologies, and innovation, are supported by the statement that 80% of executives believe that their current business models are at risk of being disrupted soon and 84% think that innovation is essential to their growth strategy (McKinsey 2018). However, only 6% of the executives are satisfied with their innovation performance (McKinsey 2018) – and in sum demonstrating the importance of a well-founded IT innovation management.

IT innovation management can be subdivided into three perspectives: IT innovation creation, adoption, and diffusion (Patrakosol and Olson 2007). Managing the creation, adoption, and diffusion of IT innovations has become an indispensable challenge since they require substantial financial funds and personnel resources but simultaneously bear considerable risks (Lu and Ramamurthy 2010; Swanson and Ramiller 2004). To ensure economically well-founded investment decisions, it is of great importance to analyze and evaluate possible IT innovation initiatives ex-ante under consideration of the involved specific costs, risks, and benefits (Häckel et al. 2017). To support this challenge, prior research focusing on the first perspective, the IT innovation creation, examines the development of IT innovations (e.g., King et al. 1994; Lyytinen and Rose 2003) and investigates, for example, how organizations can enhance the team performance of their innovation creation process in terms of quantity and quality of created IT innovations. Focusing on the adoption and diffusion of IT innovations, prior research examines, for example, how organizations can identify appropriate IT innovations, aiming at long-term strategic goals, and ensure an economically well-founded investment strategy (e.g., Fichman 2001; Swanson and Ramiller 2004). However, although organizations invest on average four percent of total revenue in innovation initiatives (PwC 2018), these investments are frequently based on a gut feeling or herd behavior. These investment strategies often lack economically well-founded evaluations and analyses, as the market for IT innovations is characterized by intense competition, unclear expectations, and an environment influenced by the hype surrounding innovations and technologies.

Following the mentioned perspectives on digital transformation and IT innovation management, the research work carried out in this doctoral thesis aims to investigate selected areas and focuses on digital transformation management (Chapter II), IT innovation management (Chapter III) and the more in-depth analysis of specific IT innovations (Chapter IV). Figure I.1-1 provides an overview of the focus areas included in this doctoral thesis.

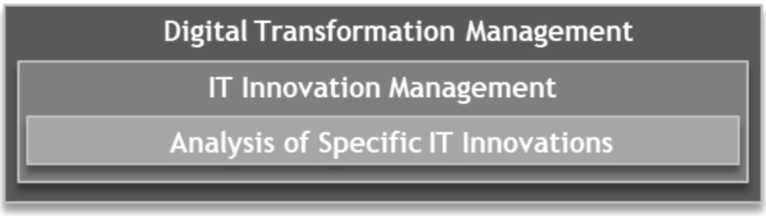

Figure I.1-1 Focus Areas of the doctoral thesis

Digital Transformation Management: Digital transformation is a form of organizational transformation (Chanias et al. 2019) and describes a paradigmatic shift in terms of a multi-dimensional change, which affects, inter alia, customer experience, business models, operational processes, and organizational structures (Gimpel et al. 2018; Hess et al. 2016; Morakanyane et al. 2017; Warner and Wäger 2019). The digital transformation journey proves to be long and winding, as the necessary changes are massive, require to overcome resistance, and are risky to fail due to its complexity (Hess et al. 2016; Uhl and Gollenia 2016). To successfully master digital transformation, organizations need to identify relevant dimensions (Hess et al. 2016) and develop transformation roadmaps (Berghaus and Back 2017; Kane et al. 2016) including activities such as the definition of a future target state and the derivation of projects to reach that state (Kane et al. 2015; Andriole 2017).

In contrast to most start-ups, which like Uber and Spotify are "born digital", particularly mature organizations must go along the path of digital transformation. The advantages of start-ups include the holistic vision of business leaders, faster innovation capability, and (already) highly digitized products and services (Wade and Shan 2016). In contrast, incumbents need to take advantage of their strengths, such as access to capital, strong confidence in the brand, and their large customer base. To successfully compete with start-ups, incumbents further need to improve their understanding and implementation of digital transformation, such as the digitization of products, services, and processes (Wade and Shan 2016).

Consequently, two-thirds of organizational leaders agreed that their organization must address digital transformation by 2020 in order to stay competitive (Gartner 2018). A prominent example of a well-established organization standing out with their digital transformation strategy is Nike. Their mobile app, the number one shopping app in China, pairs the digital and physical in-store shopping experience. Inside a retail store, customers can unlock tailored offers based on their past engagement or scan products for further information. Nike can offer customers more tailored products and experiences through the use of data analytics, e.g., by rewarding active members and utilizing demand-sensing technology. Concerning their supply chain, digital tagging and tracking of products all the way to the customer using RFID improves their value network processes (Zigurat 2019; Infotechlead 2020).

However, the success of digital transformation activities cannot be taken for granted as staggering 70% of digital transformation activities do not reach their goals, and less than one of five organizations are deemed "very effective" with digital transformation (Tabrizi et al. 2019; Harvey Nash and KPMG 2017). For example, the aspiration of Ford Motor Company to become a smart mobility provider in 2014 failed primarily since they neglected to integrate their digital transformation efforts with their traditional manufacturing business (Morgan 2019). The key reasons for failing digital transformation activities are the missing understanding among organizational leaders for the holistic organization-wide impact of their activities (Berghaus and Back 2017) and the lack of a clear vision of their transformed organization (Kane et al. 2016). The resulting absence of an organization-wide shared common understanding of digital transformation further fosters the accumulation of individual projects that do not contribute to the desired target state (Onay et al. 2018). Hence, organizational leaders need novel approaches that support them in structuring this complex endeavor and identifying capabilities that organizations need to acquire during their digital transformation (Bordeleau and Felden 2019; Matt et al. 2015). Chapter II addresses these challenges by developing a multi-dimensional maturity model to guide organizational stakeholders in addressing digital transformation on all organizational levels.

IT Innovation Management: Due to their increasingly rapid emergence and development, technological developments are an indispensable challenge for almost all organizations (Broy et al. 2012; Chui et al. 2010; Gartner 2015; Wortmann et al. 2015). As we are in an era of new technological advances, organizations need to continuously invest in the management of IT innovations to keep pace with competition and maintain sustainable long-term success. IT innovation management involves the creation, adoption, and diffusion of IT innovations (Rubera and Kirca 2017; Trkman et al. 2015).

Thereby, an essential topic in the context of IT innovation creation is the improvement of the IT innovation process, which can be defined as the process from an idea to the commercialization of an IT innovation or the so-called "idea-to-launch" process (Cooper 2008, p. 213). Thereby, a fundamental perspective is to focus on the employees assigned to those IT-related innovation projects (ITIP). Considering the team design in the ex-ante economic evaluation of ITIPs is reasonable as the overall success of an ITIP highly depends on team design factors. These factors, e.g., the team size, experience, and diversity, have a substantial effect on the ITIP's anticipated benefits and costs (Garcia Martinez et al. 2017; Hoisl et al. 2017; Horwitz and Horwitz 2007; Hülsheger et al. 2009). For example, the success chances (e.g., due to an increased probability of excellent ideas) but also the costs of a highly experienced team are apparently higher than the success chances and costs of a considerably less experienced and qualified team. The impact of the team design within ITIPs can be analyzed by applying the input-process-output model (Kozlowski et al. 2015; McGrath, 1964; West and Anderson, 1996). Thereby, input refers to the characteristics of the individual team member (e.g., knowledge and skills), the team itself (e.g., size and structure), and the organizational context (e.g., information systems and training resources). Process includes cognition-, motivation-, and behavior-based characteristics that emerge from interactions among team members. Outputs refer to the team results and can be performance-related (e.g., quantity and quality of ideas), ability-related (e.g., increase in knowledge, skills, and abilities), and affect-related (e.g., well-being and team member satisfaction) (Kozlowski et al. 2015; West and Anderson 1996). Prior studies that examine project team effectiveness concerning the input-process-output model (e.g., Gibson and Gibbs 2006; Horwitz and Horwitz 2007; Ilgen et al. 2005; Kozlowski and Ilgen 2006) focus on the empirical and non-monetary investigation of a project team's performance depending on selected design parameters. However, to allocate the financial and personnel resources in an appropriate way and to balance the associated benefits and costs in a way that supports value-based management principles (Fridgen and Moser 2013; Häckel et al. 2017), companies need a well-founded ex-ante economic evaluation of their ITIPs. Nevertheless, there exists only little support for ex-ante monetary analysis on how to design an innovation team to increase the performance of an ITIP. Moreover, the economic effects of relevant causal relationships, e.g., between team size and monetary project success, have not yet been sufficiently researched.

With a focus on the adoption of IT innovations, investments in (emerging) IT innovations also play a significant role in IT innovation management. To generate competitive advantages through such investments, an economically well-founded investment strategy is of decisive importance since timing and extent of investment amounts considerably determine the associated risk and return profile. Therefore, in a first step, it is helpful to consider the concept of "hype cycles" by Gartner Inc. (e.g., Panetta 2017), according to which different stages of maturity characterize the uncertain development of an emerging IT innovation.

The development of an *"emerging"* innovation begins with a *technology trigger* with excess publicity, leading to over-enthusiasm and investments often influenced by bandwagon behavior. Within their lifecycle of adoption (Rogers 2003), IT innovations are often "hyped" and accompanied by waves of discourse or rumors about the innovation itself as well as its adoption and diffusion (Abrahamson and Fairchild 1999). This hype typically reaches a peak of *inflated expectations* before it fades away in a *trough of disillusionment*. Investments in these development phases are associated with high risks (Zhou et al. 2005; Wind and Mahajan 1997). In this early stage, substantial adoption is missing, and evaluation based on reliable estimations of future evolution is almost impossible owing to the hype that might fade in the absence of long-term productivity. Over time, only a few IT innovations become more and more sophisticated, turning into a "*mature*" innovation and are worthy of further investment and work to understand the technology's applicability, risks, and benefits. This phase leads to a *slope of enlightenment* followed by a *plateau of productivity* (Fenn and Raskino 2008; Wang 2010). In this way, the innovation gains more and more acceptance by customers, which leads to a broader diffusion and adoption, making investments less risky (Dos Santos et al. 1995). As soon as customers have widely accepted the innovation, it has been established, i.e., *"institutionalized"*. This idea of cyclical development has prevailed in hype-cycle models that have become popular among practitioners, although the cyclical course has not yet been sufficiently empirically investigated (Jarvenpaa and Makinen 2008).

However, to support the early identification of technology hypes and the determination of a technology's life-cycle-phase, a sound research basis would be desirable. A well-founded research basis would be accompanied by a better evaluation basis for organizational investment decisions, e.g., in the pre-selection of potential innovations. Although recent literature has attempted to investigate the typical development path of technologies and thus to reproduce the typical hype cycle course, new analysis methods, e.g., by considering the time lag between scientific and practical research, may significantly improve existing approaches.

Apart from the not evidenced development path of the hype cycle, the hype cycle concept does not provide any economic investment guidance, although IT innovations substantially change their risk and return profile throughout their life cycle. Therefore, a central research question in IT innovation management, *when* and *to what extent* should an organization invest in an emerging IT innovation (Swanson and Ramiller 2004), cannot be answered by the hype cycle concept.

Chapter III addresses these challenges and provides three novel approaches. Regarding the first challenge, concerning the team performance in ITIP, it provides an ex-ante financial evaluation approach to examine the optimal team design. Regarding the other two challenges concerning the development path of and investments in IT innovations, it provides new approaches for the determination of the development path and optimal strategies for investments in IT innovations.

Analysis of Specific IT innovations:

In the context of the manufacturing sector that is subject to a dynamic digital transformation, there has been a tremendous hype built up around Industry 4.0. The term covers not a specific IT innovation, but several technological developments and innovations such as internet of things, internet of services, or cyber physical systems (Lasi et al. 2014). All these terms comprise in its inner kernel the advanced digitalization of production facilities through the digital connection of smart machines and products with networked embedded systems and the extensive integration of information systems, digital services, and internet-based technologies (Barrett et al. 2015; Schuh et al. 2014; Zuehlke 2010). Besides others, these innovations promise to increase efficiency and competitiveness by enabling the flexible production of highly customized products at costs comparable to mass production (Radziwon et al. 2014). The tremendous amount of generated production and product data enable hybrid product-service systems and innovative digital business models like pay-per-use concepts (Lasi et al. 2014). Manufacturing organizations must not only evaluate whether to invest in Industry 4.0, but especially into which specific technologies and in which order. In alignment with value-based management principles, such investments have to be evaluated ex-ante under consideration of involved costs, risks, and benefits (Häckel et al. 2017). Consequently, to lay the foundation for the development of corresponding investment and business strategies, organizations need a comprehensive picture of Industry 4.0 technologies and their contribution to value creation. In contrast to the costs and risks, however, the benefits of

Industry 4.0 have not yet been extensively analyzed in a structured way and can therefore not sufficiently be assessed for subsequent economic evaluation.

An IT innovation, which shapes new opportunities for many kinds of organizations, regardless of the specific industry, is the "business process as a service" concept. The increasing digitization of business processes, along with modern IT, allowing a fast and easy integration of business partners, leads to a continuing and radical transformation of e-business value chains as well as new and innovative forms of cooperation (Barua et al. 2001; Andal-Ancion et al. 2003; Ramirez et al. 2010). By analogy with concepts such as software or infrastructure as a service, “business process as a service” describes a dynamic business process outsourcing relationship between a business process service provider (BPSP) and its business clients: Both parties technically integrate their processes via IT-based technologies, allowing the BPSP to deliver its service within a flexible contract period and a consumption-based pricing model. Moreover, the BPSP can flexibly share its resources among different business clients in order to ensure service provision as stipulated in the applicable service level agreement (SLA). A typical example of a specific BPSP would be a payment service provider offering online identification and authorization services and electronic payment processing (e.g., Amazon Payments, PayPal).

As capacity planning, due to its volatility, is a major challenge for BPSPs, they must tackle inefficiencies in capacity planning resulting from both idle capacity and lost revenue in times of peak demand. However, the development of technologies such as service-oriented architectures, cloud-computing, and associated concepts may help mitigate this capacity planning problem. These technological developments allow business partners to interact in a highly dynamic manner and to match available excess capacity with excess demand (Grefen et al. 2006; Moitra and Ganesh 2005) – forming so-called excess capacity market (ECM). However, using excess capacity bears also risks. For instance, excess capacity’s availability can be limited, and therefore the risk of waiting times at the ECM and possible SLA-related penalties must be balanced against the potential economic benefits of an ECM. In sum, to avoid both, costly violations of the committed SLA due to capacity shortages in times of peak demand and idle costs in times of low demand, BPSP must balance internal resources adequately considering the opportunity to route certain service requests to the ECM. Approaching this complex ex-ante capacity planning by finding the right balance within this tradeoff is a major key to superior resource usage and a foundation for generating competitive advantage in cost-driven environments.

In this context, Chapter IV will provide a tailored analysis for specific IT innovations, one related to innovations in the context of the concept Industry 4.0 and the other to excess capacity markets.

In summary, the digital transformation of organizations and the related IT innovation management, as well as the analysis of specific IT innovations, poses challenges, which are addressed in this doctoral thesis. The following Section I.1 illustrates the objectives and structure of the doctoral thesis. In the subsequent Section I.2, the corresponding research papers are embedded in the research context and the fundamental research questions are highlighted.

I.1 Objectives and Structure of this Doctoral Thesis

The main objective of this doctoral thesis is to contribute to the field of Finance and Information Management by focusing on digital transformation and IT innovation management. This thesis provides novel perspectives that support the management of digital transformation and IT innovations as well as the analysis of specific IT innovations. Table I.1-1 provides an overview of the pursued objectives and the structure of the doctoral thesis.

I	**Introduction**
Objective I.1:	Outlining the objectives and the structure of the doctoral thesis
Objective I.2:	Embedding the included research papers into the context of the doctoral thesis and formulating the key research questions
II	**Digital Transformation Management (Research paper P1)**
Objective II.1:	Identifying and structuring dimensions affected by digital transformation on all organizational levels
Objective II.2:	Providing a capability-oriented development path towards digital maturity for all organizational dimensions affected by digital transformation
III	**IT Innovation Management (Research paper P2-P4)**
Objective III.1:	Improving the value contribution of IT-related innovation projects by providing a value-based, ex-ante evaluation approach that allows for optimizing their team design in the innovation creation phase by considering different team design factors
Objective III.2:	Identifying the developmental path of technologies with regard to the typical hype cycle course and exploring the time lag between scientific and practice-oriented research
Objective III.3:	Providing an economic evaluation approach to determine the optimal strategy regarding the timing of investments in an emerging IT innovation and crucial influencing factors
IV	**Analysis of Specific IT Innovations (Research paper P5-P6)**
Objective IV.1:	Identifying and structuring the anticipated benefits of digital technologies in the context of the digital transformation of manufacturing organizations
Objective IV.2:	Identifying and analyzing potential competitive advantages enabled by the usage of IT-enabled marketplaces within e-business value chains
V	**Results, Future Research, and Conclusion**
Objective V.1:	Presenting the doctoral thesis' key findings
Objective V.2:	Identifying and highlighting areas for future research

Table I.1-1 Doctoral thesis' objectives and structure

I.2 Research Context and Research Questions

In the following, the research questions of Chapters II to IV, including research papers P1 to P6 are motivated.

In Chapter II, research paper P1 identifies and structures the dimensions affected by digital transformation on all organizational levels. In Chapter III, research papers P2, P3, and P4 address the management of IT innovations. Focusing on the creation of IT innovations, P2 investigates how organizations can optimize team design with regard to the economic value contribution of IT-related innovation projects. P3 and P4 focus on the uncertain development of IT innovations. Thereby, P3 investigates hypes surrounding technology trends and the time lag between industrial and scientific research over time. P4 develops an evaluation approach to determine optimal strategies for investments in IT innovations. In Chapter IV, research papers P5 and P6 address IT innovation management more specifically by analyzing two specific IT innovations. From this perspective, P5 identifies and structures the anticipated benefits of digital technologies and IT innovations in the context of the industrial sector. Finally, P6 examines the potential of IT-enabled marketplaces to create competitive advantages in e-business value chains. Figure I.2-1 provides an overview of the research papers included in this doctoral thesis.

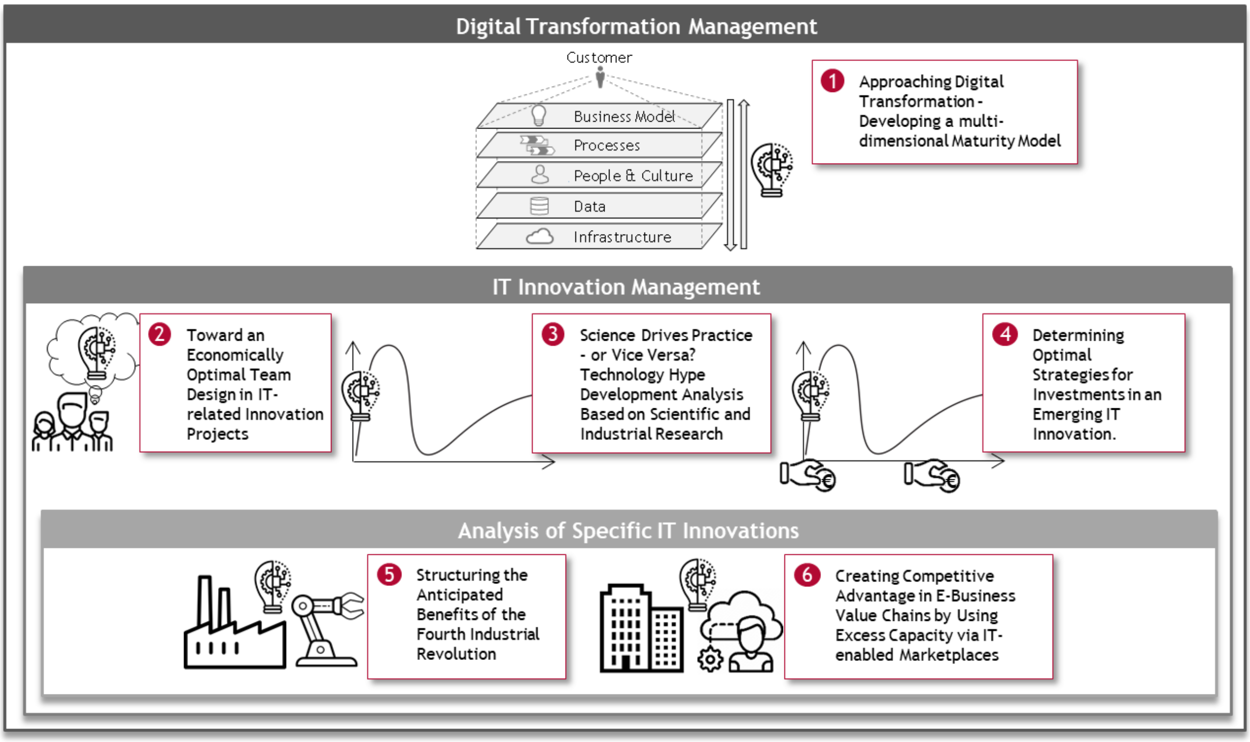

Figure I.2-1 Research papers included in the doctoral thesis – Own illustration, the upper Figure of research paper P1 as per Gimpel and Röglinger (2017)

In the following, the research papers included in this doctoral thesis are embedded in the research context, and the research questions are motivated with respect to the above stated objectives.

I.2.1 Chapter II: Digital Transformation Management

Research paper P1: *"Approaching Digital Transformation – Developing a multi-dimensional Maturity Model"*

Research paper P1 identifies and structures the dimensions affected by digital transformation (DT) on all organizational levels to guide organizational stakeholders in determining their organizations' status quo and desired target-state regarding DT.

Driven by the ever-faster emergence and adoption of IT innovations and digital technologies, organizations must transform themselves on all levels, i.e., their organizational structures, processes, work approaches, and culture (Gimpel et al. 2018). In particular, in the manufacturing industry, the transformation from traditional manufacturers of physical products to providers of individual hybrid product-service systems proves to be a complex endeavor (Urbach and Röglinger 2019; Govindarajan and Immelt 2019). However, 70% of DT projects do not deliver the desired outcome (Libert et al. 2016; Tabrizi et al. 2019) as organizations often lack a clear target vision of their transformed organization (Kane et al. 2016) and miss to develop a holistic DT strategy for an organization-wide shared common understanding of DT (Onay et al. 2018).

Existing approaches to address this challenge provide a rather high level organization perspective or focus on single organizational dimensions, but do not examine digital transformation on all organizational levels (Bordeleau and Felden 2019; Matt et al. 2015). Against this backdrop, P1 deductively and inductively derives a digital transformation maturity model, including 26 dimensions structured along six focus areas enabling the determination of an organization's current and target state of digital transformation. Thus, research paper P1 analyzes digital transformation from a holistic organization perspective and addresses Objective II.1 and II.2 from Table I.1-1 by answering the following research question:

- How can digital transformation in manufacturing organizations be approached in a structured manner?

I.2.2 Chapter III: IT Innovation Management

Research paper P2: *"Toward an Economically Optimal Team Design in IT-related Innovation Projects"*

Research paper P2 focuses on the creation of IT innovations in IT-related innovation projects (ITIPs) by providing a new approach for an ex-ante financial evaluation of ITIPs related to team design.

According to prior empirical and social-psychological research, an appropriate team design can increase team performance (e.g., Gibson and Gibbs 2006; Horwitz and Horwitz 2007; Ilgen et al. 2005; Kozlowski and Ilgen 2006). However, it remains unclear how team design can influence the monetary value contribution of an ITIP, although its economic outcome highly depends on team design factors (Garcia Martinez et al. 2017; Hoisl et al. 2017; Horwitz and Horwitz 2007; Hülsheger et al. 2009).

Such team design factors, e.g., the team size, experience, or academic background diversity, have a substantial effect on the ITIP's anticipated benefits and costs. For example, concerning the benefits, the success chances (e.g., due to an increased quantity and quality of ideas) of an experienced team are obviously higher than those of a less experienced and qualified team - in return, the project costs apparently increase.

Therefore, since team design factors considerably affect the outcome of an ITIP, organizations can benefit from finding an optimal team design by considering the counteracting benefits and costs of an associated ITIP. To assist organizations in this endeavor, P2 develops a mathematical model to examine and illustrate causal relationships of selected company- and employee-specific team design factors. By applying this model, P2 simulates and compares various scenarios of different team designs with regard to the associated expected benefits and costs of an ITIP. In sum, in accordance with Objective III.1 from Table I.1-1, research paper P2 addresses the following research questions:

- What is a company's economically optimal design of an innovation team from an ex-ante perspective related to the expected benefits and costs of an associated ITIP?
- How do selected company- and employee-specific characteristics (e.g., geographical diversity, academic background) influence the success of an ITIP?

***Research paper P3**: "Science Drives Practice – or Vice Versa? Technology Hype Development Analysis Based on Scientific and Industrial Research"*

Research paper P3 examines the development path of technologies as well as the relationship between scientific and industrial research. Researchers in the industrial and scientific sector are working on developing new technologies that are shaping today's world. During their journey to technical maturity, these technologies experience varying interests by industrial and scientific researchers. Due to the high chances and risks associated with investments in emerging technologies, it is of decisive importance for organizations to become aware of technology hype development. Organizations must therefore be supported in recognizing hypes and better assessing the progress of technological development.

To support organizations in this endeavor, all approaches dealing with the development progress of innovation explore innovation either on a product, technological, or industrial level, with all of them sharing the idea of cyclic development of innovations (Klepper 1997; Abernathy and Utterback 1978; Agarwal and Sarkar 2002). The most prominent one among these models is the Gartner Hype Cycle, introduced in 1995 (Dedehayir and Steinert 2016), that splits the development into five stages. This idea of cyclic development has found widespread adoption in so called Hype Cycle Models, which have reached popularity among practitioners, despite insufficient investigations and traceability (Jarvenpaa and Makinen 2008). Against this backdrop, P3 extends existing approaches by new analysis methods. Thereby, P3 especially considers the time lag between scientific and industrial research by collecting large amounts of paper and patent publication data on 15 technologies and the subsequent mathematical analysis. In sum, research paper P3 addresses Objective II.2 from Table I.1-1 based on the following research questions:

- Is the interest of scientific or industrial researchers leading in researching technologies?
- How can the developmental path of technologies be determined based on the interaction between scientific and industrial research?

Research paper P4: *"Determining Optimal Strategies for Investments in an Emerging IT Innovation"*

Research paper P4 focuses on the optimal strategy for investments in an emerging IT innovation. The paper provides a quantitative optimization model enabling the determination of an optimal budget allocation over time in the sense of maximizing the investment´s overall net present value (NPV).

As we are in an era of new technological advances and high competition, investments in (emerging) IT innovations have become essential for organizations to keep pace with competition and maintain sustainable long-term success (Sedera et al. 2016). At the same time, this need for continuous investments also poses significant challenges for organizations as such investments require substantial financial funds and, at the same time, are associated with considerable uncertainty given that many emerging IT innovations are likely to fail (Lu and Ramamurthy 2010; Swanson and Ramiller 2004). Due to the uncertainty regarding their future development, an early investment in emerging IT innovations is associated with high risk but offers the opportunity of high returns. For example, due to their novelty and high level of awareness, they offer the chance to achieve a high level of awareness among customers, to generate high market shares quickly, and build up much knowledge due to their early market entry. On the other hand, a later investment in rather mature IT innovations may carry lower risk, but only offers the possibility of lower or even negative returns.

Usually, organizations choose one of these pure investment strategies – a strict *first mover* (FM) or *late mover* (LM) investment strategy – often on a gut feeling or alleged market experience instead of balancing opportunities and risks within a mindful economic evaluation (Swanson et al. 2004; Wang 2010). However, a mix of both investment strategies can be advantageous, as chances and risks of pure FM and LM strategies can be balanced and therefore optimized with regard to maximizing the investment´s overall NPV. Furthermore, company- and innovation-specific factors that also have a significant influence on the risk and return profiles of investments in IT innovations are often neglected.

Therefore, due to the lack of adequate approaches, P4 aims to assist organizations in determining an economically well-founded investment strategy by considering the chances and risks of IT innovations with different maturity as well as company- and innovation-specific factors. Thus, research paper 4 covers Objective III.3 from Table I.1-1 by the following research questions:

- How can a company determine the optimal strategy for investments in an emerging IT innovation regarding the expected NPV?
- How do different company- and IT innovation-specific factors influence the optimal strategy and the expected NPV of investments in an emerging IT innovation?

I.2.3 Chapter IV: Analysis of Specific IT Innovations

Research paper P5: *"Structuring the Anticipated Benefits of the Fourth Industrial Revolution"*

Research paper P5 examines the anticipated benefits of technologies and innovations in the context of the terminology Industry 4.0, which includes concepts like cyber physical systems, smart factories, and industrial internet of things.

The adoption of emerging technologies and the associated digitalization of manufacturing organizations are anticipated to transform whole economies in a disruptive manner (Iansiti and Lakhani 2014). They promise significant benefits, e.g., increasing production efficiency by self-controlling and self-optimizing the production process in real-time (Schuh et al. 2014) and thus enabling flexible production of highly customized products at costs comparable to mass production (Radziwon et al. 2014). To deal with these developments, organizations must not only evaluate whether to invest into Industry 4.0, but especially into which specific technologies and in which order. Accordingly, investments in appropriate technologies have to be evaluated under consideration of value-based management principles – including the involved costs, risks, and benefits (Häckel et al. 2017).

As the benefits, in contrast to the costs and risks, have not yet been extensively analyzed in a structured way, P5 lays the foundation for the subsequent economic evaluation of digital technologies following value-based management principles. Therefore, a structured literature review was conducted, and the identified benefits were consolidated to 24 conclusive benefits and structured in the four dimensions *operational*, *managerial*, *strategic*, and *organizational*, using an established framework for information system benefits (Shang and Seddon 2002). Further, to ensure practical application, a discussion of managerial implications and challenges that should be considered in the strategic alignment of manufacturing organizations is presented. In sum, research paper P5 addresses Objective IV.1 from Table I.1-1 by stating the following research question:

- How can the benefits of Industry 4.0 – anticipated in scientific literature – be structured?

Research paper P6: *"Creating Competitive Advantage in E-Business Value Chains by Using Excess Capacity via IT-enabled Marketplaces"*

Research paper P6 analyzes the potential of using the IT-enabled concept of excess capacity markets (ECM) for business process service providers (BPSP).

The increasing digitization of business processes allows organizations to source whole business processes from external providers that allocate all resources necessary to ensure an effective and efficient process operation (Sengupta et al. 2006). BPSP and its business clients integrate their processes via IT-enabled technologies, allowing the BPSP to deliver its service within a flexible contract period and a consumption-based pricing model. Exemplary services are online identification services, as well as electronic payment processing (e.g., Amazon Payments, PayPal).

Within this concept, the BPSP can share its resources among different business clients, which is useful as BPSP usually face very volatile demand. At the same time, most BSPS are only partially able to react to demand fluctuations by scaling their IT capacity or their personnel resources on short notice. However, BPSP want to ensure their service level agreement (SLA) contracted with the business client, such as guaranteed processing times, to avoid SLA-related penalties. Therefore, the major challenge for BPSP is to operate cost-efficiently by finding the right balance between covering peak demand while also ensuring the efficient use of resources in times of average or low demand, which may result in idle capacity (Bassamboo et al. 2010).

To address this challenge, IT-driven capacity marketplaces may help, as they allow BPSP to interact in a highly dynamic manner with third-party providers with underutilized IT and/or personal capacities forming the ECM (Grefen et al. 2006; Moitra and Ganesh 2005). ECM allow matching available excess capacity with excess demand and therefore enable a highly dynamic and coordinated interplay of its market participants. However, using excess capacity also bears risks (Dorsch and Häckel 2014). For example, since the excess capacity’s availability can be limited, a BPSP has to consider the risk of waiting times at the ECM and must balance it against the potential economic benefits of using the ECM.

Caused by volatile demand, the BPSPs must tackle inefficiencies in capacity planning resulting from both idle capacity and lost revenue and assess the risks associated with using ECM. To examine this tradeoff and to analyze the potential of using the ECM aiming to create competitive advantages in cost-driven e-business value chains, P6 develops an analytical model based on queuing theory and evaluates it by means of possible application scenarios. Consequently, research paper P6 addresses Objective IV.2 from Table I.1-1 by stating the following research question:

- Which competitive advantages can be realized through an IT-enabled ECM within a BPSP’s value chain regarding the processing of cost-driven inhomogeneous service requests?

I.2.4 Chapter V: Results and Future Research

After this introduction, which aims at outlining the objectives and the structure of the doctoral thesis as well as at motivating the research context and formulating the research questions, the research papers are presented in Chapters II to IV. Subsequently, Chapter V presents the key findings and highlights areas for future research.

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II Digital Transformation Management

This chapter addresses digital transformation from a holistic organizational perspective. Thereby, research paper P1 *“Approaching Digital Transformation – Developing a multi-dimensional Maturity Model*” (Section II.1) identifies and structures the dimensions affected by digital transformation on all organizational levels by deductively and inductively deriving a digital transformation maturity model. Based on that, P1 provides a development path towards digital maturity for all organizational dimensions affected by digital transformation.

II.1 Research Paper 1: "Approaching Digital Transformation – Developing a multi-dimensional Maturity Model"

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Abstract: *Driven by the ever-faster emergence and adoption of digital technologies, digitalization materially affects organizations. In particular in the manufacturing industry, the development from traditional manufacturers of physical products to providers of individual digital service solutions entails changes on all organizational levels, e.g. infrastructure or business model. Despite growing awareness about the importance of digital transformation, scientific and professional literature mostly focuses on selected aspects. Yet, a holistic approach is missing which is why managers still struggle to transform their organizations in a structured way. Against this backdrop, we develop a maturity model to guide organizational stakeholders in addressing digital transformation on all organizational levels. Based on design science research principles, we deductively and inductively derive 6 focus areas, 26 dimensions and associated capabilities. To revise and evaluate our model, we conduct evaluation rounds with researchers and industry experts. Our contribution is twofold: From an academic perspective, we add to the descriptive knowledge on digital*

transformation. For practitioners, we provide a profound basis for the development of a holistic digital transformation strategy by enabling the determination of an organization's current and desired target state.

II.1.1 Introduction

Digital Transformation (DT) is primary driven by the fast emergence of digital technologies such as the Internet of Things, artificial intelligence, or cloud computing (Gimpel et al., 2018). These technologies enable organizations to create novel business models and to achieve competitive advantage (Iansiti and Lakhani, 2017; Ross et al., 2017). In fact, due to ever shorter innovation cycles and growing competitive pressure, organizations are increasingly forced to exploit the full potential of these digital technologies (Ismail et al., 2018). As a result, organizations must transform themselves as a whole, i.e. their organizational structures, processes, work approaches, and culture (Gimpel et al., 2018).

In particular in the manufacturing sector, DT proves to be a complex endeavour that entails massive changes (Urbach and Röglinger, 2019; Govindarajan and Immelt, 2019). This is because organizations need to develop from traditional manufacturers of physical products to providers of individual service solutions (Govindarajan and Immelt, 2019; Lerch and Gotsch, 2014) and from product-centred to customer-oriented in order to stay competitive (Buschmeyer et al., 2016). The Ford Motor Company is a prominent example that the success of this transformation endeavour cannot be taken for granted. Their aspiration to become a smart mobility provider in 2014 failed primarily since they neglected to integrate their DT efforts with their traditional manufacturing business (Morgan, 2019). However, this case is not an exception. Experts estimate that 70% of DT projects do not deliver the desired outcome (Libert et al., 2016; Tabrizi et al., 2019), as most organizational leaders struggle to understand the holistic impact of DT (Berghaus and Back, 2017). Furthermore, they lack a clear vision of their transformed organization (Kane et al., 2016). While digital mature organizations have a holistic long-term DT strategy and leverage technologies to change the way they do business, struggling organizations focus on the short-term implementation of individual technologies (Kane et al., 2015). Thus, the absence of a holistic DT strategy and an organization-wide shared common understanding of DT are causes for failure (Onay et al., 2018), i.e. a collection of single projects that do not contribute to the desired target state or inefficient usage of investments.

Hence, there have been calls from research and practice to structure the field of DT (Bordeleau and Felden, 2019). In scientific literature, various approaches for the development of DT strategies are discussed (Matt et al., 2015; Hess et al., 2016; Chanias, 2017). Other approaches derive action fields (Gimpel et al., 2018; Gimpel and Röglinger, 2017), success factors (Holotiuk and Beimborn, 2017), or challenges (Piccinini et al., 2015b; Heavin and Power, 2018) that organizations need to consider during their DT. Another research stream provides detailed maturity models (MM) that outline a development path towards a desired target state (Schumacher et al., 2019; Schuh et al., 2017; Berghaus and Back, 2016a; Lichtblau et al., 2015; Klötzer and Pflaum, 2017). Professional literature provides various frameworks that present transformation paths and MMs for affected areas including tools that support organizations in assessing their status quo (PWC, 2016; Gill and van Boskirk, 2016; Zimmermann et al., 2015; Azhari et al., 2014).

Even though we do not doubt the value of existing approaches, they either provide a too abstract perspective, solely focus on operational aspects or the assessment of the status quo, or do not publish details on their frameworks' dimensions and development process. Hence, there are no guidelines that support managers in both structuring this complex endeavour and identifying capabilities that organizations need to acquire during their DT (Bordeleau and Felden, 2019; Matt et al., 2015). Against this backdrop, we address the following research question:

How can digital transformation in manufacturing organizations be approached in a structured manner?

To answer our research question, we follow the well-established procedure model of Becker et al. (2009), which is based on design science research principles (Hevner et al., 2004), to develop a digital transformation maturity model (DTMM) as an artefact. We derive our DTMM deductively by conducting a structured literature review, and inductively by performing interviews with industry experts and focus group discussions. To evaluate our artefact, we draw on the evaluation activities proposed by Sonnenberg and vom Brocke (2012). Our artefact adds to the descriptive knowledge on DT and serves practitioners as an initial step to approach their DT in a structured manner.

The remainder of this paper is structured in line with the procedure model as per Becker et al. (2009): In Section II.1.2, we provide our theoretical background along with related work *(comparison of related MMs*). Section II.1.3 describes our research methodology *(determination of the development strategy* and *iterative MM development process).* In Section II.1.4, we present the DTMM as the core of our work. Our evaluation activities are presented in Section II.1.5. In Section II.1.6, we summarizes our results and contribution, and gives an outlook on future research.

II.1.2 Theoretical Background and Related Work

DT is a form of organizational transformation (Chanias et al., 2019) and describes a paradigmatic shift in terms of a multi-dimensional change, which affects, inter alia, customer experience, business models, operational processes, and organizational structures (Gimpel et al., 2018; Hess et al., 2016; Morakanyane et al., 2017; Warner and Wäger, 2019). DT takes time and effort, needs to overcome resistance, and, due to its complexity (Hess et al., 2016), is risky to fail (Uhl and Gollenia, 2016). To successfully master DT, organizations need to identify relevant dimensions of DT (Hess et al., 2016) and develop a system of aligned activities (Berghaus and Back, 2017; Kane et al., 2016) such as the definition of a future target state and the derivation of strategies to reach that state (Kane et al., 2015; Andriole, 2017). A DT strategy supports organizations to identify promising activities and also facilitates their prioritization and implementation through resource allocation (Matt et al., 2015; Yeow et al., 2018).

While well-established IT strategies provide guidance for the adoption of digital technologies, they cannot be used for DT since their aim is limited to the alignment of technologies to business needs. Digital business strategies are also not suitable as they neglect organizational implications to develop and run digital business (Bharadwaj et al., 2013). DT strategies, in contrast, primarily address the question of how organizations need to transform themselves to stay competitive under consideration of fast emerging digital technologies (Kane et al., 2017; Hess et al., 2016; Chanias et al., 2019). Matt et al. (2015) state that the DT strategy needs to be aligned with the operational, functional, and corporate strategy. Under consideration of financial aspects, they propose changes in value creation and organizational structure to exploit the potential of emerging digital technologies. Based on these insights, Hess et al. (2016) outline different options for the development of a DT strategy with regard to technology adoption, e.g. early adopter.

To make digital progress measureable, Andersen and Ross (2016) and El Sawy et al. (2016) conduct case studies to identify success factors. One of their key findings is that digital leaders do not transform their organizations at once, but continuously adjust selected action fields to the requirements of the fast changing environment. To provide a solid foundation for DT in the first place, multiple contributions deal with the identification of affected action fields. Gimpel and Röglinger (2017) distinguish five layers of the enterprise architecture, i.e.

business model, processes, people and application systems, data, and infrastructure, which organizations need to transform with regard to changes of customer needs and the application of digital technologies. Gimpel et al. (2018) structure DT into six high-level action fields. Other works focus on the illumination of select action fields such as customer (Piccinini et al., 2015a; Setia et al., 2013), operational processes and business models (Berman, 2012; Westerman et al., 2014), or people (Bouée, 2015; Singh and Hess, 2017). On a fine-grained level, Warner and Wäger (2019) identify dynamic capabilities that support organizations to master their DT endeavour. Rossmann (2018) define eight capability dimensions (e.g. strategy, leadership, and technology) for which they outline underlying items (e.g. executives support the implementation of the digital strategy as item for leadership), which describe a digital mature organization. Although the presented approaches elaborate on DT from different perspectives, they lack a structured overview of DT dimensions and associated capabilities that support stakeholders in determining their organization’s status quo and desired target state.

MMs fulfil this requirement by depicting a sequence of discrete levels, i.e. dimensions and capabilities (Poeppelbuss and Röglinger, 2011), that represent an anticipated or desired evolution path from an initial state towards a future target state (Becker et al., 2009). Literature distinguishes between descriptive (assessing status quo and deriving future target state), comparative (benchmarking), and prescriptive MMs (enabling development of a roadmap) (Bruin et al., 2005). Thereby, MMs measure and guide an organization’s continuous improvement of different organizational resources such as technology, processes, or people in a specific domain (Poeppelbuss et al., 2011). A commonly accepted assumption of MMs is that the transformation path emerges linearly based on predictable evolution patterns. Therefore, the respective maturity level rises with increasing capabilities (Becker et al., 2009). While some publications explicitly state that one capability is superior to another, maturation can also be defined as the development towards the better.

In the IS domain, several MMs deal with DT: Berghaus and Back (2016a) examine DT from a holistic perspective and describe eight dimensions (e.g. strategy, organization, and customer experience) and 25 underlying sub-dimensions (e.g. digital commitment and strategic innovation as sub-dimensions of strategy). In contrast to competing MMs, they do not outline pre-defined maturity levels, but assign them by means of a cluster analysis. Azhari et al. (2014) define eight dimensions along five general maturity levels that mostly address similar aspects like Berghaus and Back (2016a). For each dimension, they describe the target state of a completely transformed organization. Other MM explicitly address DT in the context of manufacturing and focus on select topics such as products (Anderl and Fleischer, 2015), production (Anderl and Fleischer, 2015; Sjödin et al., 2018; Weber et al., 2017), logistics (Sternad et al., 2018), and organizational aspects (Fettig et al., 2018; Canetta et al., 2018). Klötzer and Pflaum (2017) present two distinct multi-dimensional MMs for the DT of internal operations and value creation to customers. Schumacher et al. (2019) structure DT into nine dimensions (e.g. technology and products) along with underlying maturity items (e.g. utilization of additive manufacturing) and integrate their MM into a procedure model towards digital maturity. With a focus on cultural aspects, Schuh et al. (2017) provide a multi-dimensional MM towards a learning and agile organization. Besides technology, Leineweber et al. (2018) also address cultural aspects with respect to the organization and the employees. Although we do not question the value of these contributions, the majority lacks details about their research methodology. Also they often do not include maturity levels. Even though MMs are a valid approach to guide organizations through their DT, none of the identified MMs provides a holistic and structured overview of the capabilities that organizations need to acquire during their DT.

Hence, organizational leaders in the manufacturing industry still struggle to structure DT and, thus, often fail to develop successful DT strategies. Although implications are intensively discussed in literature, the field of DT remains opaque. Academia still lacks a framework that considers relevant organizational dimensions and corresponding capabilities for change. To address this research gap, we develop a multi-dimensional MM, which provides structure and guidance for stakeholder to determine their organization’s status quo and future target state regarding DT, and, based on that, to develop a holistic DT strategy (Berghaus and Back, 2016a).

II.1.3 Research Methodology

For the development of our DTMM, we follow the procedure model of Becker et al. (2009). Based on the design science research principles proposed by Hevner et al. (2004), the procedure model includes eight steps (Figure II.1-1):

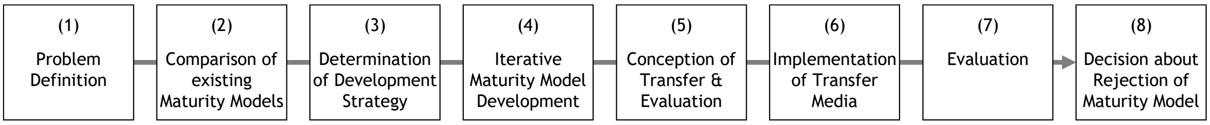

Figure II.1-1 Maturity Model Procedure as per Becker et al. (2009)

The *(1) problem definition* comprises the determination of the application area and the problem relevance. The second step requires the *(2) comparison of existing MMs* to outline the relevance for the development of a MM by pointing towards a research gap in existing publications. The third step comprises the *(3) determination of the development strategy* and its documentation. Thereby, Becker et al. (2009) differentiate between four strategies, i.e. design of a new model design, enhancement of an existing model, combination of models to form a new one, and the transfer of existing models to new application domains (Becker et al., 2009). The central step of the procedure model comprises the *(4) iterative MM development*. The *(5) conception of transfer and evaluation* incudes the evaluation of the model and defines how to make the MM accessible for intended users. Within the *(6) implementation of the transfer media* the MM is made accessible to defined user groups in an appropriate way. Based on the MM's application, the *(7) evaluation* examines whether the MM delivers the aspired solution of the problem (Becker et al., 2009). Based on the evaluation, the *(8) decision about rejection of the MM* is conducted.

In this work, we focus on step 1 to 4, whereas step 5 to 8 will be part of future research. Within Section II.1.1 and II.1.2, we already outlined the need for an appropriate DTMM *((1) problem definition)* and the lack and insufficiency of existing approaches *((2) comparison of existing MMs)*. In the following, we present our development choices and procedure *((3) determination of the development strategy* and *(4) iterative MM development)* in detail:

As for the *(3) determination of the development strategy*, there exists no MM in literature, which identifies all relevant dimensions for the DT in manufacturing. Hence, we develop a novel, descriptive MM as an artefact based on the insights of existing MMs and additional literature. Instead of defining general maturity levels, we strive for dimension-specific development paths that outline capabilities dedicated to the characteristics of a specific dimensions as proposed by van Steenbergen et al. (2010). Therefore, we aim to provide individual guidance for the broad range of different organizational areas.

Thus, in addition to Becker et al. (2009), we consider van Steenbergen et al. (2010) within the *(4) iterative MM development* phase, as they provide additional guidance for the development of dimension-specific development paths. To develop a valid model for research and practice, we use a multi-methodological approach including literature reviews, expert interviews as well as internal and scientific focus group discussions. For our iterations, we distinguish between a conceptual-to-empirical and empirical-to-conceptual approach (Nickerson et al., 2013). The deductive conceptual-to-empirical approach draws on literature and on the researchers' knowledge. In this case, we conceptualize our artefact without considering input from practice. In contrast, within the inductive empirical-to-conceptual approach, we consider the practical perspective and adjust the artefact accordingly (Nickerson et al., 2013). Our iterative MM development phase comprises four iterations (Figure II.1-2).

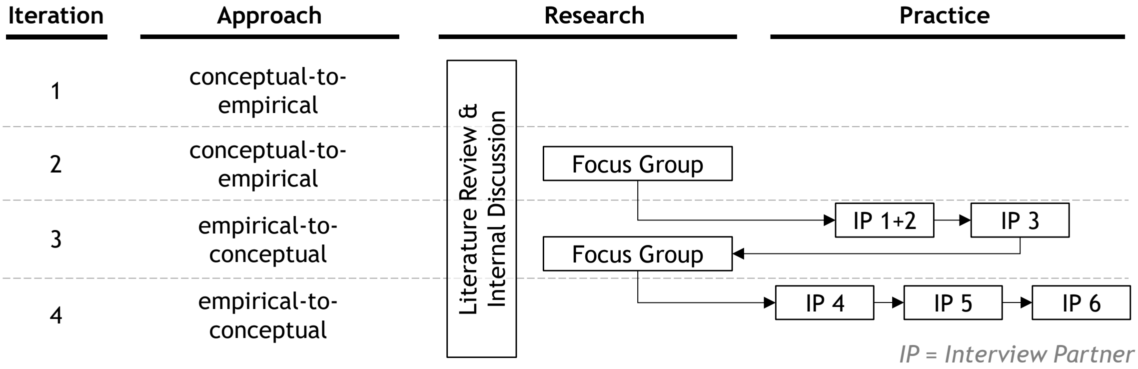

Figure II.1-2 Iterative Development Process of the Digital Transformation Maturity Model

In line with van Steenbergen et al. (2010), we deductively derive dimensions within our *first iteration* (conceptual-to-empirical). For this, we conduct a structured literature review to identify frameworks that deal with DT (Table II.1-1). Thereby, the search term Industry 4.0 comprises technological developments in the context of manufacturing companies, such as Internet of Things or cyber physical systems (Lasi et al., 2014). Our search *includes* abstract, title, and keywords as this search strategy is supposed to deliver contributions focusing on the target topic (Bandara et al., 2011). To assure a high quality of results, we initially limit our review to journals and conferences proceedings, which are classified at least as 'recognised academic business research journals' within the Sections *General Management* and *Business & Information Systems Engineering* of the *VHB JOURQUAL 3*[1]. We exclusively review articles in English and German. Subsequently, we analyse the abstracts of the remaining articles to select those that primarily focus on DT. In a last step, we extend our approach with a forward and backwards search of promising articles and conduct a full text screening to identify those articles that structure DT into different dimensions. This left us with 17 frameworks from which we derive an initial list of 342 items that, however, are not distinct and show no uniform level of granularity. Thus, we cluster the initial list of 342 items into dimensions of uniform granularity. To enhance the clarity and accessibility of our artefact, we cluster these dimensions into superordinate focus areas as proposed by vom Brocke and Rosemann (2015). We iteratively refine the focus areas and dimensions until we achieve consensus among all co-authors.

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[1] Ranking based on the evaluation of the members of the German Academic Association for Business Research

Criterion	Characteristic
Databases	Science Direct, EBSCOhost, ProQuest, AIS e-Library
Search Field	Title, Abstract, Keywords
Search Term	(“Digital Transformation” OR “Digitalization” OR “Digitization” OR "Industry 4.0" OR "Industrie 4.0" OR “Digital Strategy”) AND (transformation)

Table II.1-1 Criteria of our Structured Literature Review

Within our *second iteration*, we strive for deductively deriving capabilities for each identified dimension (conceptual-to-empirical). Therefore, we review MMs that we gathered during the ‘comparison of existing MMs’. Whenever there is no suitable MM available, we derive maturity paths using the insights from our structured literature review and knowledge acquired via additional literature searches. The derivation of capabilities also contributes to the refinement and specification of our dimensions. In addition, we discuss our artefact with a focus group of researchers and use the gained insights for revising our artefact. The focus group included one associate professor, seven research assistants, and three students from two different universities. All members shared an IS background. Focus group discussion are an effective method to collect feedback within the development phase of an artefact and to challenge it’s utility (Tremblay et al., 2010).

To include a practical perspective on DT, we evaluate our artefact in the course of interviews with industry experts within our *third iteration* (empirical-to-conceptual). Expert interviews collect information from potential users of an artefact (Rowley, 2012). Table II.1-2 provides details of our interview partners (IP), which we ensure to hold a strategic position. Furthermore, their organization must be deeply engaged with DT. To offset potential bias, we select experts from different manufacturing sectors. The interviews last about 90 to 120 minutes each and are hosted by at least two co-authors. To close the feedback loop, we again consult the same focus group to discuss our artefact’s adjustments.

IP	Job Title	Industry	Employees (2018)	Revenue (2018)
1	Product Line Director	Automotive	> 110,000	EUR 17.5 bn.
2	Director Global Industrial Strategy			
3	Senior Manager Digitalization	Mechanical Engineering	> 2,300	EUR 0.5 bn.
4	Head of Digital Business	Optics and Optoelectronics	> 27,000	EUR 5.8 bn.
5	Chief Enterprise Architect	Information Technology	> 32,000	EUR 4.1 bn.
6	Chief Technology Officer	Car Wash Manufacturing	> 2,300	EUR 0.4 bn.

Table II.1-2 Details on Industry Experts

As the *third iteration* still implied major changes, we discuss the DTMM with three industry experts within our *fourth iteration* (empirical-to-conceptual). This leads to only minor changes, i.e. adjustment of the nomenclature. As the four co-authors and the questioned experts agree that the artefact is concise, robust, and comprehensive, we refrain from conducting another iteration and end the development process.

To validate the usefulness of our artefact, we include semi-structured questions (Schultze and Avital, 2011; Myers and Newman, 2007) in our interviews, which ask the experts about the applicability of our artefact and also challenge the general approach of our research project. The questions were in line with established evaluation criteria as per Sonnenberg and vom Brocke (2012). We summarize our evaluation results in Section II.1.5.

II.1.4 Digital Transformation Maturity Model

In this Section, we present our DTMM as the core of our work. Our DTMM consists of focus areas, dimensions, and capabilities, which organizations need to address to make necessary structural changes and changes in value creation to successfully perform DT (Matt et al., 2015). We present our results as follows: Firstly, we describe the overarching structure of our DTMM and explain how to read it. Secondly, we describe each focus area and associated dimensions in detail.

To provide a high-level structure for DT dimensions, we analyse extant frameworks and architectures which describe organizational levels. We follow Gimpel and Röglinger (2017) to illustrate six focus areas and their relations (Figure II.1-3): To exploit the full potential of digital technologies, organizations need to adjust their *Infrastructure* and develop capabilities to leverage the growing amount of *Data*. Corresponding changes affect an organization's *People & Culture* and offer opportunities to improve *Processes*. The adaption of the *Business Model* to *Customer* needs plays a key role for DT.

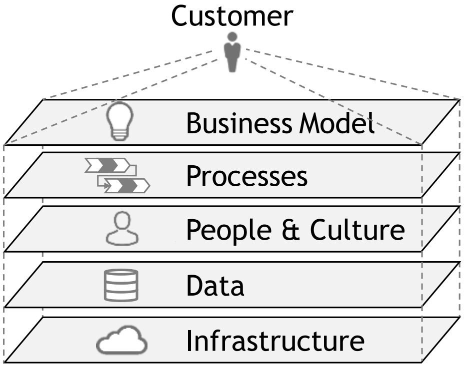

Figure II.1-3 Focus Areas of the Maturity Model as per Gimpel and Röglinger (2017)

To face the challenges of today's business environment, organizations need to address all focus areas within an integrated approach. Even though organizations can select a specific focus area as starting point (Berghaus and Back, 2017), the organizational levels are interrelated. Thus, organizations need to introduce an organization-wide transparent and accepted DT strategy (Rossmann, 2018), which is aligned with the organizational purpose and other organizational strategies (Matt et al., 2015). This implies dividing the complex organizational transformation as a whole into manageable projects, defining corresponding roles and decision making processes, and measuring the progress of the transformation process continuously. Considering the holistic purpose of the DTMM, the focus areas are not focused on certain parts of the organization, but should take a holistic view on the organization. For example, People & Culture does not only address the human resources department but the organization as a whole.

Our core artefact, the DTMM (Table II.1-3) comprises organizational capabilities with respect to 26 dimensions that are clustered into the six focus areas. For each dimension, we outline the corresponding capabilities. The relevance of a capability depends on the particular context of application, the organization-specific business strategy, and the underlying business model. Even though none of the capabilities is per se ‘better’ than another one, the acquisition of capabilities contributes to maturity since organizations have the freedom to choose the most appropriate among their acquired capabilities for a specific context. Accordingly, on the lowest level, organizations possess only the capability that is outlined within the first column. On the second level, organizations have additionally acquired the capability, which is stated within the second column, and so on. The sequence of the capabilities refers to the target of organizations to become more data-driven, agile, and customer-oriented during their DT. To enhance scientific documentation, we outline references that we used to derive the capabilities for each dimension within Table II.1-3 (references stated in italic provide a MM, other references provides different characteristics).

<table>
<tr><th>Focus Area</th><th>Dimension</th><th colspan="20">Capabilities</th><th>References</th></tr>
<tr><td rowspan="3">Infrastructure</td><td>IT Infrastructure</td><td colspan="5">Function-specific Infrastructure</td><td colspan="5">Service-oriented Architecture</td><td colspan="5">Cloud Platform</td><td colspan="5">Inter-organizational Infrastructure</td><td>(Berghaus and Back, 2016b, 2017; Colli et al., 2019; Gimpel et al., 2018; Holotiuk and Beimborn, 2017; Klötzer and Pflaum, 2017; Piccinini et al., 2015b; Schuh et al., 2017)</td></tr>
<tr><td>IT Security</td><td colspan="5">Isolated IT Security Activities</td><td colspan="5">Security of Highly Critical Assets</td><td colspan="5">Security of Processes</td><td colspan="5">Security by Design</td><td>(D'Arcy et al., 2009; Musman et al., 2011; Purdy, 2010; Regal et al., 2018; Silva et al., 2012; Subashini and Kavitha, 2011)</td></tr>
<tr><td>IT Department</td><td colspan="5">Functional IT</td><td colspan="5">Business Integrated IT</td><td colspan="5">IT as Service Provider</td><td colspan="5">IT as Driver of Change</td><td>(Berghaus and Back, 2017, 2016a; Coltman et al., 2015; El Sawy et al., 2016; Klötzer and Pflaum, 2017; Holotiuk and Beimborn, 2017; Piccinini et al., 2015b; Wheeler, 2002)</td></tr>
<tr><td rowspan="3">Data</td><td>Data Collection</td><td colspan="5">No Collection</td><td colspan="5">Manual Collection</td><td colspan="5">Partially Automated Collection</td><td colspan="5">Fully Automated Collection</td><td><i>(Neff et al., 2014; Schumacher et al., 2019; Schuh et al., 2017)</i></td></tr>
<tr><td>Data Aggregation</td><td colspan="5">Raw Data</td><td colspan="5">Target Data</td><td colspan="5">Pre-processed Data</td><td colspan="5">Transformed Data</td><td><i>(Fayyad et al., 1996; Gimpel et al., 2018; Schuh et al., 2017; Holotiuk and Beimborn, 2017)</i></td></tr>
<tr><td>Data Analysis</td><td colspan="4">No Analysis</td><td colspan="4">Descriptive Analysis</td><td colspan="4">Diagnostic Analysis</td><td colspan="4">Predictive Analysis</td><td colspan="4">Prescriptive Analysis</td><td>(Ardolino et al., 2018; Porter and Heppelmann, 2015; Gimpel et al., 2018)</td></tr>
</table>

Focus Area	Dimension	Capabilities					References
	Data Integration	No Integration	Partial Integration	Integration with Major Business Entities	Integration with Whole Enterprise	Integration Beyond Enterprise	*(Neff et al., 2014; Sternad et al., 2018; Gimpel et al., 2018; Schumacher et al., 2019; Colli et al., 2019)*
People & Culture	**Digital Skills**	No Digital Skills	Recruiting Digital Skills	Educating Digital Skills	Developing Digital Leaders		(Berghaus and Back, 2016a, 2016b, 2017; Gimpel et al., 2018; Holotiuk and Beimborn, 2017; Kagermann et al., 2013; Kane, 2017; Schuh et al., 2017; Schwarzmüller et al., 2018)
	Workplace Environment	Desk Space	Meeting and Social Space	Collaborative Space	Spaces beyond the Building		(Berghaus and Back, 2016a, 2016b, 2017; El Sawy et al., 2016; Gimpel et al., 2018; Harris, 2015; Waber et al., 2014)
	Organizational Structure	Function-oriented hierarchical Structures	Cross-functional Projects	Product-/Process-oriented Organization	Independent, self-organized Teams		(Berghaus and Back, 2016b; Bilgeri et al., 2017; El Sawy et al., 2016; Gimpel et al., 2018; Holotiuk and Beimborn, 2017; Kane et al., 2016; Libert et al., 2016a; Mankins and Garton, 2017; Schwarzmüller et al., 2018; Yoo et al., 2012)
	Innovation Culture	Inhibition of Innovation	Openness towards Change	Acknowledgement of Experimentation	Aspiration to Improvements	Entrepreneurial Thinking	(Berghaus and Back, 2016a, 2016b; Bilgeri et al., 2017; El Sawy et al., 2016; Gimpel et al., 2018; Hartl and Hess, 2017; Holotiuk and Beimborn, 2017; Kane et al., 2015, 2016; Piccinini et al., 2015b)
	Leadership	Top-Down Governance	Transformational Leadership	Servant Leadership	Coaches & Sponsors		(Andriole, 2017; Baldomir and Hood, 2016; Bass, 1990; Berghaus and Back, 2016b, 2017; Gimpel et al., 2018; Holotiuk and Beimborn, 2017; Hartl and Hess, 2017; Kane et al., 2016; Oldham and Da Silva, 2015; Spreitzer, 1995; Schwarzmüller et al., 2018)
Processes	**Process Control**	Instinct-driven Decisions	Data-based Decisions	Autonomous Decisions			(Colli et al., 2019; Gimpel et al., 2018; Holotiuk and Beimborn, 2017; Kane et al., 2016; Klötzer and Pflaum, 2017; Müller et al., 2018; Schuh et al., 2017)
	Production Flexibility	Rigid Production Systems	Adaptive Production Systems	Component-driven Production	Modular Production across Value-adding Network		(Anderl and Fleischer, 2015; Gimpel et al., 2018; Lichtblau et al., 2015)
	Product Assembly	Small Proportion of Identical Parts	High Proportion of Identical Parts	Modular Construction of Products	Modular Products		(Anderl and Fleischer, 2015; Gimpel et al., 2018; Schumacher et al., 2019; Schuh et al., 2017)
	Business Processes Flexibility	Rigid Processes	Flexibility within Individual Processes	Interaction of Processes	Interaction across the Value-adding Networkk		(Gimpel et al., 2018; Schumacher et al., 2019; Schuh et al., 2017)
	Inter-organizational Collaboration	Linear Supply Chain	Provider Network	Partner Network	Digital Ecosystem		(Berghaus and Back, 2016a, 2016b, 2017; Bilgeri et al., 2017; El Sawy et al., 2016; Gimpel et al., 2018; Ibarra et al., 2018; Klötzer and Pflaum, 2017; Libert et al., 2016b)
Business Model	**Offering**	Product	Standard Service	Novel, additional Services	Product-as-a-Service	Result-as-a-Service	(Anderl and Fleischer, 2015; Bilgeri et al., 2017; Ehret and Wirtz, 2017; Gimpel et al., 2018; Ibarra et al., 2018; Klötzer and Pflaum, 2017; Lerch and Gotsch, 2014; Michalik et al., 2018; Neff et al., 2014; Richter et al., 2017; Übelhör, 2019; Weking et al., 2018; Govindarajan and Immelt, 2019)
	Pricing Strategy	(Fixed) one-time Price	Periodic Fee	Usage-based Billing	Performance-based Billing		(Colli et al., 2019; Ehret and Wirtz, 2017; Fleisch et al., 2015; Gassmann et al., 2014; Müller et al., 2018; Rapaccini, 2015; Scherrer et al., 2017; Weking et al., 2018)
	Target Market	Existing Customers in existing Markets	New Customers in existing Markets	New Customers in additional Markets	Creation of new Markets		(Arnold et al., 2017b; Ibarra et al., 2018; Kiel et al., 2017; Weking et al., 2018; Übelhör, 2019)

Focus Area	Dimension	Capabilities						References
	Sale Channel	Traditional Channels		Web-based Channels		Product as Point-of-Sales		(Kiel et al., 2017; Poeppelbuss and Durst, 2017; Übelhör, 2019; Schumacher et al., 2019; Fleisch et al., 2015)
	Distribution Channel	Physical Delivery of Product		Physical Delivery of Service		Digital Delivery of Service		(Arnold et al., 2016, 2017a; Fleisch et al., 2015; Lim et al., 2018; Michalik et al., 2018; Mittag et al., 2018; Poeppelbuss and Durst, 2017; Porter and Heppelmann, 2015; Scherrer et al., 2017; Schumacher et al., 2019)
Customer	**Customer Insights**	No Information	Anonymous Information		Segment-specific Information	Personalized Information		(Berghaus and Back, 2016b; Gimpel et al., 2018; Westerman et al., 2014)
	Customer Integration	No Integration	Integration of Feedback	Integration in Early Design Process	Design Process as Co-Creation	Ideation Phase as Co-Creation	Partner-like Collaboration	(Exner et al., 2018; Fleisch et al., 2015; Holotiuk and Beimborn, 2017; Übelhör, 2019; Arnold et al., 2016; Kiel et al., 2017)
	Customer Interaction	Personal Interactive Interaction	Self-Service		Digital, Semi-automated Interaction	Automated Interaction		(Beverungen et al., 2019; Fleisch et al., 2015; Müller et al., 2018; Scherrer et al., 2017; Übelhör, 2019; Schumacher et al., 2019)
	Customer Experience	Isolated Touchpoints		Aligned Touchpoints		Personalized Experience		(Berghaus and Back, 2016a, 2016b; Berman, 2012; Bilgeri et al., 2017; Gimpel et al., 2018; Holotiuk and Beimborn, 2017; Müller et al., 2018; Piccinini et al., 2015b; Westerman et al., 2014)

Table II.1-3 Digital Transformation Maturity Model

In the following, we outline the focus areas in more detail and provide a brief description of each dimension. To foster clarity and readability, we describe the focus areas from technical matters to strategic aspects:

An organization's **Infrastructure** serves as a foundation for organizational structures, processes, and business models. While in the past the focus of IT was to support and maintain the availability of operational processes, today agility, interoperability, and scalability are desirable characteristics of the *IT Architecture* (Bilgeri et al., 2017; Piccinini et al., 2015b). Accordingly, organizations need to replace function-specific legacy systems by service-oriented architectures that are continuously adapted to business needs (Bilgeri et al., 2017; Piccinini et al., 2015b). Implementing cloud platforms and inter-organizational infrastructures raises new challenges for *IT Security*. Since novel business models are built upon data-driven processes, it is crucial to sustain operations and build trust in the organization (Gimpel et al., 2018). Hence, isolated IT security activities may not be sufficient anymore. Organizations need to identify their critical assets, secure their processes end-to-end, and start to consider the security of their infrastructure by design. Since DT is driven and enabled by digital technologies, the corresponding transition of the *IT Department*, i.e. from a functional unit towards an internal service provider, contributes to an increasing organizational agility. To leverage the full potential provided by novel digital technologies, the IT Department increasingly needs to act as a driver of change that identifies business needs and implements suitable solutions to solve them (El Sawy et al., 2016).

Data is often described as the new currency (Bilgeri et al., 2017) and can be the foundation for value creation and competitive advantages (Bharadwaj et al., 2013; Gimpel et al., 2018). The adoption of digital technologies provides various opportunities for *Data Collection*, which is a key activity for data-driven organizations and business models (Lim et al., 2018). However, since data does not provide any value per se, organizations need to develop additional capabilities (Lim et al., 2018). *Data Aggregation* outlines the steps to acquire valuable knowledge from data (Fayyad et al., 1996). The value of data depends on the kinds of insights organizations derive from *Data Analysis* (Ardolino et al., 2018). While descriptive analysis supports decisions, e.g. via visualization, prescriptive analysis proposes suitable decision alternatives and their corresponding impact. To capture the potential value of the data, the acquired knowledge needs to be integrated into processes and decisions. Therefore, *Data Integration* into major business entities or even beyond the organization improves planning and execution of decisions (Porter and Heppelmann, 2015).

To leverage digital technologies and the huge amounts of data, organizations need to initiate structural and cultural changes in terms of **People & Culture** (Andersen and Ross, 2016). While the handling of digital technologies like artificial intelligence new abilities, organizations need to acquire employees with *Digital Skills* (Schwarzmüller et al., 2018). At the same time, organizations need to continuously develop their employees' skill set to keep pace with ever increasing environmental changes. Therefore, they need to develop digital leaders, which drive that change and identify new opportunities (Kane et al., 2017). Since digital talents are rare, *Workplace Flexibility* will help organizations to retain such leaders and attract new employees. This dimension describes the degree to which the working environments contributes to efficient collaboration within the organizational borders and beyond. The performance of the organization and its ability to continuously adapt to a changing environment depends also on its organizational structures (Libert et al., 2016a; Schwarzmüller et al., 2018). *Organizational Structure* describes the transformation from a solely hierarchical work approach towards more independent and self-organized teams that dynamically adapt to changing requirements. To adopt novel technologies and quickly react to changing customer needs, organizations need to develop an *Innovation Culture* that fosters innovation and agility, and contributes to a learning organization (Gimpel et al., 2018). *Leadership* shapes the organizational culture (Kane et al., 2017) and is therefore an essential part of the DT. Organizational leaders increasingly need to empower their employees and enable them to drive projects by themselves.

Besides organizational structures, organizations need to adapt their **Processes** to successfully face the challenges of today's business environment (Holotiuk and Beimborn, 2017). The use of digital technologies and data builds the foundation for autonomous *Process Control* (Gimpel et al., 2018; Holotiuk and Beimborn, 2017). To become agile, organizations strive for *Business Process Flexibility*, i.e. increase flexibility within individual processes as well as ensure adaptability between processes within and beyond the organizational borders (Gimpel et al., 2018). As product lifecycles become shorter and the individualization of products becomes increasingly important, organizations need to produce small batch sizes efficiently to stay competitive (Gimpel et al., 2018). While *Production Flexibility* represents the adaptability of the production equipment to changing product characteristics, *Product Assembly* describes the degree to which organizations can adapt their product design to customer needs (Schuh et al., 2017). Since digital business models rely on data-driven services which enhance physical products, organizations need to cooperate with their value-adding network to provide the best possible solution to their customers (Berghaus and Back, 2017). Thereby, the nature of *Inter-organizational Processes* transforms from a linear supply chain to digital ecosystems (Arnold et al., 2017b), in which partners and customers are integrated in an increasingly interactive and collaborative way (Ibarra et al., 2018).

Digital technologies enable organizations to create new **Business Models** that deliver additional value to customers (Bilgeri et al., 2017). With respect to servitization, the *Offering* changes. Former manufacturers of physical products integrate additionally data-driven services and provide results as a service to satisfy customer needs (Bilgeri et al., 2017). Accordingly, the risk for achieving a certain result shifts from the customer to the provider. This transformation implies that the product remains property of the provider, who needs to develop new *Pricing Strategies* to capture the value from its offering. Novel offerings provide the opportunity to extend the *Target Market* in terms of addressing new customers, additional markets, or even creating new markets. While customers may continue to buy the physical product via traditional or web-based channels, digital capabilities increasingly enable the physical product to serve as a *Sales Channel* for supplementary services (Übelhör, 2019). While the distribution of the traditional product will remain physical, the *Distribution Channel* for additional services can be increasingly detached from a physical location (Lim et al., 2018).

To maximise customer value and generate competitive advantages, organizations increasingly need to align their operations and activities towards **Customer** needs. Hence, organizations collect and analyse customer data to generate *Customer Insights*, which serve as a foundation to offer individual solutions (Gimpel et al., 2018). *Customer Integration* describes the degree to which the customer is part of the design and development process of a product. With rising maturity, customers evolve from consumers to partners, especially with regard to collaboration, as well as co-design and development (Übelhör, 2019; Berghaus and Back, 2017). Digital technologies offer the opportunity to perform operational parts of the *Customer Interaction* in automated and autonomous ways (Beverungen et al., 2019). *Customer Experience* is characterized by the subjective feeling of customers towards an organization and its offerings (Gimpel et al., 2018). To retain customer loyalty, organizations need to offer a consistent and personalised experience throughout all customer touchpoints.

II.1.5 Evaluation and Application

We evaluated and validated our DTMM as follows: Firstly, as part of our development process, we continuously evaluated our artefact by conducting focus group meetings and expert interviews. Secondly, we asked the same stakeholders to challenge evaluation criteria from design science research. Thirdly, we give some ‘food for thought’ on how to apply the DTMM and embed it within a DT strategy.

Within our iterative development process, we conducted interviews with two focus groups and six industry experts, which helped us to revise our artefact. In the following, we present selected annotations:

- As the adoption of digital technologies is a central driver of DT (Gimpel and Röglinger, 2017; Matt et al., 2015), we discussed its inclusion as a focus area with both focus group members and industry experts. Striving for long lasting insight, we aimed to create an artefact which is independent from short-term technology trends. For some dimensions, however, the utilization of technology is implicitly considered (e.g. cloud platform)
- Within our first focus group meeting, some researchers pointed out the need for a distinctive and intuitive nomenclature. As the prior version of our DTMM still comprised overlapping capabilities (e.g. basic and partial data integration) or different rationales within one dimension (e.g. for the dimension data integration: time such as real-time integration, and scope such as partial integration), we revised the artefact accordingly. In addition, our capabilities, dimensions, and focus areas should be comprehensible without further explanations or requiring a digitalisation background. Therefore, we replaced technical terms like two-speed IT. To close the feedback loop, we consulted the same focus group within our third iteration.

- Initially, our artefact included the overarching focus area ‘DT management’. With capabilities like the definition of roles and responsibilities, our experts stated that these are considerable characteristics of an organizations. However, they argued not to integrate the management into the DTMM as it is more of a prerequisite for change. Hence, we abandoned this focus area.
- During the interviews, we adjusted the way how to read our DTMM. Based on the insights of the experts, we concluded that not a certain capability represents the highest maturity level for each dimension. In contrast, the highest maturity level means that organizations have acquired all capabilities within a dimension and, thus, have the freedom to choose one or several capabilities that fit best within the current situation. Regarding the dimension ‘business process flexibility, for instance, an organization which achieved the capability ‘interaction of processes’ is also able to implement ‘rigid processes’. As flexibility might increase the possibility of errors, it could be reasonable to also create some ‘rigid processes’ for critical tasks in addition to interacting processes. This means that, depending on the current situation, organization’s need to choose and combine certain capabilities to achieve the desired target state. Moreover, the experts pointed out that although we develop a DTMM, not all capabilities necessarily have a digital nature.

To evaluate the procedure of building our artefact, we additionally added semi-structured questions to our interviews which are in line with evaluation criteria as per Sonnenberg and vom Brocke (2012). We enriched the interview results with insights from our literature review and our focus group meeting with researchers. Table II.1-4 gives an overview of our results.

Finally, as part of our evaluation, we also discussed with our experts how the DTMM contributes to concrete activities and an overall DT strategy. As proposed in scientific literature (Schumacher et al., 2019; Schuh et al., 2017), the DTMM should be an integral part of a transformation path. With our DTMM at hand, stakeholders first have to determine the status quo of their organization. Based on the definition of long-term strategic objectives, the target state, i.e. associated dimensions and capabilities, can be determined. Comparing the status quo with the future target state will support organizations in deriving company-specific projects. Subsequently, the individual projects need to be prioritised, sequenced, and carried out. To monitor the DT and to measure the degree to which projects have achieved their objectives, the dimensions and capabilities of our DTMM should be subject to continuous re-evaluation.

Evaluation Criteria	**Evaluation Method**	**Findings**
Novelty and importance of the problem	Literature Review, Expert Interview, Focus Group Discussion	As DT significantly differs from traditional organizational transformations, our literature review revealed that the majority of organizations lacks a holistic DT strategy. Due to the opacity within this fast-moving field, organizations still struggle to understand the implications of DT (*novelty*). A common understanding, however, is a prerequisite to identify relevant action fields to successfully transform an organization. The experts confirmed the insufficiency of existing approaches to structure the field. Being researchers in the field of digitalization, the focus group also emphasized the need for descriptive knowledge on DT (*importance*).
Understandability, and suitability	Expert Interview, Focus Group Discussion	The experts and focus group members stated that a MM is suitable for representing capabilities, dimensions, and focus areas of a DT in a structured, comprehensible, and intuitive manner (*understandability, suitability*). They, in particular, pointed out the benefit of our idea of using descriptive names to guide intended users, rather than providing only numerical scales. Thereby, our capability definition offers a flexible and company-specific configuration of capabilities and the corresponding transformation path.
Ease of use, operationality, and robustness	Expert Interview, Focus Group Discussion	To test our artefacts applicability in an artificial setting, we asked our focus group and industry experts to challenge our capabilities sequence and granularity. The interviewees confirmed the suitability and understandability of our method to classify their activities (*ease of use*). However, the experts remarked that the user friendliness could benefit from providing additional descriptions and examples of the capabilities, as well as introducing the DTMM stepwise as at first sight stakeholders might be overstrained. As we see this as part of our models implementation in terms of a management tool, it exceeds the scope of this work. As for *operationality*, our experts stated that our artefact could be integrated as part of existing DT strategies (cf. the end of this Section for details) to evaluate the status quo and target state of an organization. IP2 suggested to introduce the DTMM with workshops or even implement it as part of a management tool to provide additional guidance. To provide stable results (*robustness)*, we defined capabilities that are independent of short-term technology trends.
Applicability and fidelity with real world phenomena	Expert Interview	To validate the DTMM's usefulness in a naturalistic setting, we asked our interview partners to classify their organization's status quo by means of our DTMM. Since the determination of the respective actual state was feasible

Evaluation Criteria	Evaluation Method	Findings
		and reflected the organizations' situation, the experts confirmed the *fidelity with real-world phenomena*. Besides, we asked the experts about the *applicability* of our approach. The answers were manifold: The experts would use the DTMM, inter alia, to assess the status quo and develop their targets state (all experts), to discuss action fields with the top-management to raise funding (IP6), and as a foundation to develop DT KPI's, e.g. the degree of process autonomy (IP2). Besides managers, the artefact supports stakeholders on all focus areas, e.g. product and business model developer (IP4). Independent of specific use cases, our experts concluded that the DTMM offers a holistic view on relevant dimensions and capabilities for the DT.

Table II.1-4 Details on Evaluation Criteria

II.1.6 Conclusion

We motivate our study by arguing that the fast emergence of digital technologies and associated effects on the business environment force industrial organizations to digitally transform themselves. The lack of descriptive knowledge, however, hampers scientific progress and practical applications. Against this backdrop, we follow the 'design science research'-based procedure model as per Becker et al. (2009) to develop a DTMM as an artefact. Our DTMM includes 26 dimensions structured along six focus areas to guide organizational stakeholders in determining their organizations' status quo and desired target-state regarding DT. We developed our artefact within several iterations, which build on an extensive literature review, internal discussions, and insights from scientific focus group discussions and interviews with industry experts. We structured the evaluation of our DTMM along the evaluation activities as per Sonnenberg and vom Brocke (2012).

We contribute to the descriptive knowledge on DT. Our findings build on and extend current discussions on DT strategies and related action fields, e.g. Matt et al. (2015); Hess et al. (2016); Gimpel et al. (2018). By summarizing, enriching, and structuring academic literature in this field, we provide researchers and practitioners with an overview of and common nomenclature for DT dimensions and capabilities. Our holistic DTMM includes details on focus areas, dimensions, and capabilities which organizations need to consider for their DT strategies. Thereby, we argue that maturity in the context of DT does not exclusively comprise digitization, but also includes other rationales, e.g. flexibility. Regarding the professional literature, we extend high-level transformation paths and MMs like PWC (2016). While these frameworks provide a foundation for initially grasping the topic, they lack a deep-dive into DT dimensions and capabilities, which is necessary to address DT entirely and in detail. Moreover, existing frameworks and MMs are not based on a structured development process, but rather represent loose collections of terms. Our DTMM, in turn, is the result of a rigorous research process. With this, we hope to provide a profound basis for future research within this fast-moving field. As the majority of our dimensions is not manufacturing-specific, we also contribute to other research streams which investigate the DT in other contexts.

Our DTMM is also meant to support and guide intended users in transforming their organizations: In general, our artefact allows managers to capture their organization's status quo concerning DT. Based on the organization's objectives, users can derive their future target state and associated capabilities within each dimension and focus area. This, in turn, enables the derivation of individual projects which contribute to a DT strategy to reach the desired target state. Our artefact supports managers in making informed decisions about the selection and prioritization of DT projects, and at the same time, increases the transparency of the associated decisions. In sum, our artefact helps to reduce an organization's uncertainty in dealing with DT and enables them to stay competitive in a dynamic environment.

As with any research project, our DTMM is beset with limitations which stimulate future research. Firstly, we recognize that digital technologies and the business environment constantly evolve and change over time. We accounted for this by creating dimensions and capabilities on an abstract level of granularity. However, as our framework is extendable, it should be subject to continuous re-evaluation and adjustment in the future. Secondly, although we follow a procedure model and conduct a multi-methodological approach, the development of the DTMM might suffer from potential bias concerning literature selection and author's judgement. Hence, our artefact will benefit from further validating activities. In particular, the application on real-world use cases could be useful to access our DTMM's fidelity to real-world phenomenon. Thirdly, certain DT projects require combining certain capabilities. Hence, our work could be extended through subsequent development steps proposed by van Steenbergen et al. (2010) to identify interrelated dimensions and capabilities.

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III IT Innovation Management

The first research paper P2 in this Chapter “*Toward an Economically Optimal Team Design in IT-related Innovation Projects*” (Section III.1) provides an approach for an ex-ante financial evaluation of IT-related innovation projects (ITIPs) related to team design. P2 develops a mathematical model for determining the optimal team design of an ITIP that is evaluated by simulations, sensitivity analyses, and interviews with practitioners. P2 examines relevant causal relationships by analyzing the influence of team design factors on the theoretical optimum. Further, to illustrate the model’s applicability in a real-life scenario, the model is applied to a scenario of a financial services start-up.

The second research paper P3 *“Science Drives Practice – or Vice Versa? Technology Hype Development Analysis Based on Scientific and Industrial Research”* (Section III.2) examines the relationship between scientific and industrial research for the recognition of technology development paths. Therefore, P3 collects large amounts of paper and patent publication data on 15 technologies by a self-developed automated webscraper and examines the data with methods of time series analysis (ARMA and ARMAX).

The third research paper P4 *“Determining Optimal Strategies for Investments in an Emerging IT Innovation”* (Section III.3) develops a model for an ex-ante financial evaluation to determine optimal strategies for investments in an emerging IT innovation. The model considers investments at an early stage as a first mover (FM), later investments as a late mover (LM) as well as “mixed” strategies, in terms of timing and investment volume. Optimal investment strategies may outperform strict FM or LM strategies concerning the investment’s expected NPV. Further, P4 considers company- and IT innovation-specific factors and evaluates the model in several possible investment scenarios.

III.1 Research Paper 2: "Toward an Economically Optimal Team Design in IT-related Innovation Projects"

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Abstract: *Driven by an increased relevance of the digitalization in almost all business activities and ever-competitive business environments, companies need to focus on IT-related innovation projects (ITIP) in order to guarantee long-term success. Although prior research has illustrated that an appropriate team design can increase the team performance, it remains unclear how team design can influence an output of an associated ITIP. Existing research examines either project team performance in a non-monetary view or open innovation communities with a focus on external factors. This paper contributes to research by developing a model that determines the optimal team design for an ITIP by transferring central findings of previous research regarding relevant influencing factors into an economically evaluation and a comparison of different project designs with regard to their profitability. We examine relevant causal relationships by analysing the influence of team design factors on the theoretical optimum. We find that ITIPs with near optimal team designs have considerably higher profits than projects with random team designs. To increase the profit, companies should balance benefits and costs related to the innovation team design. The results provide an indicator for the team designing in practice and a starting point for future research.*

III.1.1 Introduction

In today’s globalized business environment, competitive pressure as well as the need for innovations that are indispensable to guarantee a long-term competitive advantage are steadily increasing. The pervasive digitalization forces even low-tech companies to deal with emerging technologies like the internet of things (IoT) or big data as new digital business models and innovative IT-based products and services are indispensable for companies to survive in competitive environments, reduce costs and improve margins (Schilling 2010; Yoo et al. 2010). Thus, companies increasingly run IT-related innovation projects (ITIPs) in order to capture first-mover benefits in a highly competitive market. For example, automotive companies shift their business models from carmakers to mobility service providers, financial service providers expand their offer through IT-based, data-driven services and even platforms for further service providers. Manufacturers run various innovation initiatives to digitalize their factories and to adopt IoT in their business models (Bürger and Moser 2017).

However, ITIPs are often linked with high investment amounts in their early phases and a high uncertainty regarding their expected future outcome and cash flows. Furthermore, their potential to disrupt entire business models and industries increase their strategic importance. On the one hand, ITIPs that aim at developing new and better IT-related products or services, can increase a company’s innovativeness and profits. However, they also can easily lead to considerable losses if they are set on a gut-feeling (Bürger and Moser 2017). To handle this challenge, companies need a well-founded ex-ante economic evaluation of their ITIPs to allocate the financial and personnel resources in an appropriate way and to balance the associated benefits and costs in a way that supports value-based management principles (Fridgen and Moser 2013; Häckel et al. 2017).

Considering the team design in the ex-ante economic evaluation of ITIPs is quite reasonably as the overall success of an ITIP highly depends on team design factors - e.g. on the team size, experience and diversity - since they have a substantial effect on the ITIP’s anticipated benefits and costs (Garcia Martinez et al. 2017; Hoisl et al. 2017; Horwitz and Horwitz 2007; Hülsheger et al. 2009). For example, the success chances (e.g. due to an increased probability of excellent ideas) but also the costs of a highly experienced team are apparently higher than the success chances and costs of a considerably less experienced and qualified team. Additionally, the team size has obviously a strong influence on the benefits and costs of an ITIP. Thus, an economically well-founded ITIP setting has to consider and balance the trade-off between benefits and costs related to the associated team design. Prior studies that examine project team effectiveness (e.g. Gibson and Gibbs 2006; Horwitz and Horwitz 2007; Ilgen et al. 2005; Kozlowski and Ilgen 2006) indeed investigate a project team's performance depending on selected design parameters. However, there exists only little support for ex-ante analysis on how to design an innovation team to increase the performance of an ITIP. Moreover, the economic effects of relevant causal relationships have not yet been sufficiently researched. Finally, prior research rather focuses on discussing which team design parameters encourage creativity and innovation on the individual, team or organizational level of analysis (for a more detailed discussion see Hülsheger et al. 2009) and neglects the project level.

To contribute to the closure of the research gap regarding an economically well-founded design of an innovation team by considering the counteracting benefits and costs of an associated ITIP, we derive our first research question:

RQ1. *What is a company's economically optimal design of an innovation team from an ex-ante perspective related to the benefits and costs of an associated ITIP?*

As previously described, the overall success of an ITIP depends on various team design parameters. Considering the diverging effects of those parameters on benefits and costs, the question of which company-specific and employee-specific characteristics have a substantial influence on the success of the ITIP's result - a new IT-related product or service - needs to be answered. This raises our second research question:

RQ2*. How do selected company- and employee-specific characteristics (e.g., geographical diversity, academic background) influence the success of an ITIP?*

To answer the research questions, we develop a mathematical model that is able to illustrate relevant causal relationships and to examine them analytically. It also allows comparing different team designs with regard to the associated expected profit of an ITIP. Based on this analysis, we are able to give first answers toward an optimal design of an ITIP team. This approach is closely related to Meredith et al. (1989) who state that for research fields that have not been examined yet, mathematical models and quantitative approaches can serve as a basis for future research questions and empirical research. Furthermore, several external influences (e.g. missing data, political reasons) in practice often lead to a somewhat coincidental ITIP team design rather than a rational, strategic decision. Therefore, we apply sensitivity analyses and analyse a wide range of possible scenarios to examine the economic impact of different team designs on the ITIP profit. Our model delivers first answers on this almost unexamined research field and illustrates the influence of several factors on the associated benefits and costs. To underpin our model assumptions with practical experience and to challenge the model's fit to practice, we conducted interviews with two practical experts. Both experts work in senior management positions and are conversant with designing innovation project teams. The first expert is from a large industrial company, the second one from a small start-up company in the financial services industry. By this, we further ensure that our model can be applied for different industries as well as company sizes. As the economic evaluation of ITIPs related to team design is only one possible perspective, our approach aims at stimulating investigations of the impact of the team design on ITIPs performance and serves as a basis for further research of such relationships in further terms.

The paper is organized as follows: First, we provide an overview of relevant literature. After that, we develop and analyse our theoretical model to answer the stated research questions. We conclude by discussing the contributions to research and practice, limitations and future research potential.

III.1.2 Theoretical Background and Related Work

As teams play a crucial role in innovation projects, prior research has widely investigated how an innovation team should be designed to increase its performance. Therefore it is not surprising that the research body on the relationship between the team design and its performance is rich. For analysing the impact of team design on the associated output, the input-process-output (IPO) model of team performance is a widely used approach, particularly in the innovation literature (Hackman 1987; Hülsheger et al. 2009; Kozlowski et al. 2015; McGrath 1964; West and Anderson 1996). Thereby, *inputs* refer to characteristics of the individual (e.g., knowledge, skills, and abilities and demographics), the team (e.g., size and structure), and the organizational context (e.g., tasks and objectives, information systems, and training resources). *Processes* include cognition-, motivation-, and behaviour-based characteristics that emerge from interactions among team members and that impact the team outcome. *Outputs* refer to the team results and can be performance-related (e.g., quantity and quality of ideas), ability-related (e.g., increase in knowledge, skills, and abilities), and affect-related (e.g., well-being and team member satisfaction) (Kozlowski et al. 2015; West and Anderson 1996). In our approach, we focus on selected inputs and performance-related outputs in innovation projects, which aim at generating new IT-related innovations that are defined as '[…] innovations in the organizational application of digital computer and communications technologies' Swanson (1994).

Whereas the prior research has widely addressed the importance of team design for innovation (Hackman 1987; Hülsheger et al. 2009), the number and definition of considered input parameters vary. For example, West and Anderson (1996) identified team member diversity, team size, and tenure as important antecedent conditions of innovation. Hülsheger et al. (2009) extended these parameters through task and goal interdependence to encourage interpersonal interaction, communication, and cooperation within the team.

Especially team diversity is widely discussed in the prior research. First, various forms of team diversity have been provided. For example, Hülsheger et al. (2009) define two diversity manifestations: job-relevant diversity and background diversity. Thereby, job-relevant diversity 'refers to the heterogeneity of team members with respect to job- or task-related attributes, such as function, profession, education, tenure, knowledge, skills, or expertise' and background diversity 'describes non-task-related differences such as age, gender, or ethnicity' (Hülsheger et al. 2009, p. 1129). Garcia Martinez et al. (2017) also consider diversity from two perspectives: surface and deep-level diversity. Thereby, surface-level diversity means 'differences among group members in overt, biological characteristics that are typically reflected in physical features' (Harrison et al. 1998, p. 97) and deep-level diversity refers to 'differences amongst group members' psychological characteristics, such as cognitive abilities, attitudes, values, knowledge and skills' (Garcia Martinez et al. 2017, p.312). Despite the different terms, the prior research generally divides diversity in a demography-related (e.g., age, gender and race/ethnicity) and job- or task-related dimension (e.g., education, knowledge and skills).

Regarding the impact of diversity on team performance, the prior research reveals indications for both, positive and negative impact. On the one side, diversity can increase the team performance as teams with diverse members bring together a broad array of expertise, skills, and knowledge that support them in solving complex tasks like developing new products, processes or services (Garcia Martinez et al. 2017; Horwitz and Horwitz 2007; Hülsheger et al. 2009). Different perspectives and approaches can further stimulate creativity-related cognitive processes (Perry-Smith 2006) and avoid the negative impact of groupthink (Hoisl et al. 2017; Janis 1972). Finally, diverse teams can broaden their cognitive resources through further information and additional perspectives by means of communication with members outside the team (Perry-Smith and Shalley 2003; West 2002) and integrate new knowledge in order to generate new ideas due to greater absorptive capabilities (Cohen and Levinthal, 1990). On the other side, diversity can reduce team performance. For instance, diversity can lead to communication problems caused by different knowledge backgrounds and jargons (Dougherty 1992) as well as difficulties in resolving opposing ideas and consequently, in reaching consensus within the team (Garcia Martinez et al. 2017; Hülsheger et al. 2009). Moreover, diverse teams can lack intra-group trust due to low social integration and task conflicts (Richard et al 2007). These challenges can lead to increased communication and coordination costs (Garcia Martinez et al. 2017; Reagans and Zuckerman 2001) and to a slow-down of the innovation process (Hoisl et al. 2017).

Although most research on team effectiveness focuses on face-to-face teams, increased globalisation and advanced IT have fostered working in virtual teams (Kozlowski et al. 2015), also for innovation teams. Virtual teams can be defined as ‘geographically dispersed, electronically dependent, dynamic, or comprising diverse members working remotely’ (Gibson and Gibbs 2006, p. 451). Innovation teams can profit from geographic dispersion as they can get relevant expertise from around the globe (Kirkman et al. 2002) and, thus, are able to achieve a more comprehensive understanding of global markets (e.g. customers and suppliers) (Boutellier et al. 1998; Gluesing and Gibson 2004). Virtual team members further provide diverse backgrounds, knowledge, expertise and perspectives that can be integrated into new products and services (Dougherty 2001; Gibson and Gibbs 2006; Nohria and Berkley 1994; Nonaka and Takeuchi 1995). At the same time, diverse backgrounds such as cultural differences can lead to challenges in communicating and building shared understandings (Hinds et al. 2011; Kozlowski et al. 2015).

The prior research on the impact of team size on team performance also provides different insights. For example, Hülsheger et al. (2009) and Stewart (2016) state that team size is positively related to innovation as larger teams provide a wider array of diverse viewpoints, skills, and perspectives. Hülsheger et al. (2009) further refer to similar insights in other research areas like a positive link between organization size and innovation and a positive relationship between team size and innovation in the brainstorming literature. In contrast, West and Anderson (1996) state that the teams should have sufficient, but not greater than the sufficient number of members to perform a task. Whereas small teams lack the diversity needed for innovation, large teams impede effective interaction, exchange, and participation due to the increasing complexity of the communication structure between team members (West and Anderson 1996; Zenger and Lawrence 1989). Despite the different findings, the prior research notes that the team size is one of the key influencing parameters for team performance (Garcia Martinez et al. 2017; Pelled et al. 1999; Sethi et al. 2001).

Similar to team *inputs,* prior research provides different insights for team *outputs*, particularly for team performance as a measure for the effectiveness of members’ observable goal-directed team behaviour (Kozlowski et al. 2015). In general, measuring the performance of an innovation team is rather challenging as it is difficult to link the output of an innovation team to innovation success. Moreover, there exists no universal approach for measuring the impact of team design on team performance. For example, Garcia Martinez et al. (2017) measure innovative performance as the percentage of the firm's total sales from innovations. Horwitz and Horwitz (2007) consider several outcome measures for team performance such as quantitative production, qualitative team outcomes and team cohesion. Despite the different approaches to measure team performance, there is an agreement that it can be positively influenced by an appropriate team design. As our approach aims at analysing how an appropriate team design can increase the performance of an ITIP, we measure the team performance as an economic performance of an ITIP.

Concluding, we can state that many prior studies focus on analysing the impact of one concrete team design parameter, mostly team diversity, on the team performance. Furthermore, empirical research with focus on ex-post analyses considerably predominates. Finally, the authors use different definitions of team performance in their analyses, whereby innovation performance is mostly measured on the individual, team and organisational level. Thus, despite the rich knowledge body on team design and team performance, there still exists a lack of approaches that support ex-ante analysis on team design in order to increase the team performance on the project level. Although the innovation processes are idiosyncratically emergent, unpredictable and dynamic, and it is challenging to predict the innovation output, companies still need profound guidance on how to design their innovation teams to increase the success of their ITIPs. We contribute to closure of this research gap and provide an approach that supports companies in ex-ante designing their innovation teams in order to increase the profit of ITIPs. Our approach should help to model and analyse relationships between selected team design parameters and project success. Further, it should allow an ex-ante analysis of how different design variants are likely to affect costs and benefits of an ITIP. We are aware that not all team design parameters and performance components can be explicitly measured through cash flows. However, such factors can be incorporated within a second step (Irani and Love 2002). Despite some limitations, economic evaluation illustrates important economic trade-offs and supports a mindful analysis, even if its outcome might not be convertible in practice without some adjustments or restrictions.

III.1.3 Toward an Optimal ITIP Team Design

III.1.3.1 Research Methodology

We base on a normative analytical modelling approach outlined by Meredtih et al. (1989), which captures the essentials of a decision problem by mathematical representations to produce a prescriptive result. This type of analysis supports structuring decision problems, resolving trade-offs among different criteria and a well-founded choice between decision alternatives (Keeney and Raiffa 1993). Thereby, the relevant decision variables, constraints as well as non-trivial assumptions must be transparently defined (Cohon 2004). Following this research paradigm, we develop a mathematical model that aims at determining the optimal team design of an ITIP. By considering the selected team design parameters, our model is able to analyse the trade-off between the associated costs and benefits.

To set the theoretical base for our model's assumptions, we at first consult (empirical) research mainly dealing with team effectiveness, team design and team performance to support our model assumptions (e.g. Gibson and Gibbs 2006; Horwitz and Horwitz 2007; Ilgen et al. 2005; Kozlowski and Ilgen 2006). Furthermore, as work teams 'interact socially, exhibit task interdependencies, maintain and manage boundaries, and are embedded in an organizational context', literature on work teams is also applicable in our context (Kozlowski and Bell 2003). To provide a practical evidence for the model assumptions, we interviewed two practical experts

Next to the analytical modeling, we apply a simulation-based approach to analyse the relevant causal relationships between the profit of an ITIP and the identified team design parameters. For that purpose, we conduct different univariate sensitivity analyses and a multivariate simulation. According to Meredith et al. (1989) and Davis et al. (2007), simulations are a legitimate way to analyse complex interrelationships. We also applied our model for a real-life case within an interview with the second expert to illustrate the applicability of our approach in practice. By doing so, we deliver first answers to this unexplored research topic. However, to strengthen the findings of our work, further empirical evaluation in a given organizational context is needed (Meredith et al. 1989; Wacker 1998).

III.1.3.2 Model

In our model, we consider a company that aims to generate new ideas and, thus, innovations with the help of an ITIP. Hence, this company ex-ante evaluates an ITIP compared to a previous ITIP carried out by its R&D department. Therefore, to enhance comparability, the desired type of innovation (e.g. new product or new service) should be the same as in the previous project carried out by the R&D department. By means of our model, we aim to cover the essential influencing factors and dependencies that affect the expected benefit and costs of the ITIP. We assume that the outcome of the idea generation process will be developed further throughout the whole innovation process. On this basis, the company can decide ex-ante how to design the ITIP team with regard to the influencing factors, to maximize the expected overall profit connected with the outcome of the ITIP. The major goal of our model is to illustrate and analyse the underlying causal relationships that drive the expected overall success of an ITIP.

Assumption 1 - Relevant ITIP design parameters: There is no general agreement in literature on which parameters are the most relevant for successful teamwork. However, according to their widespread discussion in literature, we focus on four relevant team design parameters for creative tasks with a highly uncertain output (Gibson and Gibbs 2006; Horwitz and Horwitz 2007; Mathieu et al. 2008; Stewart 2016): the team size, the work experience, the academic background diversity, and the geographical diversity of the different team members. Although there is a broad variety of other possible parameters (e.g. gender and age of team members), we in a first step focus on these parameters to reduce the complexity of the model and to ensure interpretability of the results. In addition, parameterization by the company is easier in contrast to factors like moral attitude or work motivation of the team members.

A) Team size: Within an ITIP, the team size / number of team members is reflected by $\mathrm{P} \in \{2,3,..,\mathrm{n}\}$. P is fixed, non-dynamic and these persons are not divided into sub teams. All team member engage comparably in the project.

B) Work experience: Each team member has its own work experience $\mathrm{w_i}$ that reflects the project-relevant industry experience in years. Consequently, the complete team's work experience is reflected by the vector $\vec{\mathrm{w}}^{\mathrm{T}} = (\mathrm{w_1}, \mathrm{w_2}, \ldots, \mathrm{w_P}) \in \mathbb{R}^+$ with the team's mean work experience $\mathrm{w_m} = \frac{1}{\mathrm{P}} \sum_{\mathrm{i}=1}^{\mathrm{P}} \mathrm{w_i}$ and the standard deviation of $\mathrm{w_d} = \sqrt{\frac{1}{\mathrm{P}-1} \sum_{\mathrm{i}=1}^{\mathrm{P}} (\mathrm{w_i} - \mathrm{w_m})^2}$ which reflects the teams' work experience diversity.

C) Academic background diversity: The degree to which the academic background of each team member coincides with each one's of the other team members is reflected by the matrix AD with $\mathrm{a_{ij}} \in [0, 1]$, where $\mathrm{a_{ij}} = 1$ describes a completely homogeneous academic background and $\mathrm{a_{ij}} = 0$ a completely heterogeneous academic background between two team members. Thereby, values between 0 and 1 have to be determined by expert's assessments. If, for instance, two persons have a similar, but not identical academic background, $\mathrm{a_{ij}}$ would be assigned a value close to 1 and vice versa. In sum, the team's academic background diversity equals $\mathrm{a} = \sum_{\mathrm{i}=1}^{\mathrm{P}} \sum_{\mathrm{j}=1}^{\mathrm{P}} \mathrm{a_{ij}} - \mathrm{P} * (\mathrm{P}^2 - \mathrm{P})^{-1}$ where $\mathrm{a} = 1$ describes a completely homogeneous and $\mathrm{a} = 0$ a completely heterogeneous team with regard to the academic background.

D) Geographical diversity: The geographical diversity is an essential factor for companies that are locating their operations in different regions or countries and/or are distributing their IT innovations globally. Analogous to the academic background diversity, we measure the geographical diversity with the help of a matrix GD with $g_{ij} \epsilon [0, 1]$. Thereby, g_{ij} reflects the degree to which the regional market assessment capabilities of each team member coincide with each ones of the other team members. Therefore, $g_{ij} = 1$ implies that the team members work in the same department and can easily meet up in person. Furthermore, we can assume that they have the same regional market assessment capabilities. In contrast to that, $g_{ij} = 0$ implies that the team members have completely heterogeneous regional market assessment capabilities and that they obviously work in different regions. Analogous to the academic background, values between 0 and 1 have to be determined by expert's assessments. If, for instance, two persons work in the same region, but not in identical department, g_{ij} would have a value close to 1 since the regional market assessment capabilities would be very similar. Vice versa, if two persons work in different regions with extremely deviating regional market needs, g_{ij} would have a value close to 0. The team's geographical background diversity is $g = \sum_{i=1}^{n} \sum_{j=1}^{n} g_{ij} - P * (P^2 - P)^{-1}$ where $g = 1$ reflects a completely homogeneous team and $g = 0$ a completely heterogeneous team with regard to the geographical background.

Assumption 2 - Costs of an ITIP: In the following, we differentiate between initial and running costs.

A) Initial Costs: Within the ITIP, there exist cash outflows for initiation costs $IC > 0$ that, among other things, include all expenditures for communication platforms as well as the workplace equipment to run a geographical diversified ITIP.

B) Running Costs: Within the ITIP, there exist cash outflows for the running costs $RC > 0$ which, among other things, include personnel expenses within the project duration.

Assumption 3 - The effect of the team size and work experience on the running costs: The total running costs $RC(P, w_m)$ of an ITIP depend on the team size and the team's mean work experience. Thereby, the company's individual personal expense $RC_{P_i} \epsilon \mathbb{R}^+$ represents the personal costs of one person with one year of work experience. To determine the total running costs, these costs need to be multiplied with the number of tem members P as well as with the mean work experience $w_m^{S_i}$, which is adjusted for the company's individual salary structure $S_i \epsilon \mathbb{R}^+$. The company's individual salary structure describes the relationship between work experience and associated salary level and may be either linear with $S_i = 1$, concave with $S_i <$

1, or convex with $S_i > 1$ - representing a proportional, under-proportional, or over-proportional increase in costs with increasing work experience. Furthermore, we assume that the running costs for different degrees of academic background diversification and geographical diversification are negligible. In sum, the total running costs equal $RC(P, w_m) = RC_{Pi} * P * w_m^{S_i}$.

Assumption 4 - The effect of geographical diversity on initial costs: The initial costs to run an ITIP depend on the team's geographical diversification and follow a piecewise function: $IC(g) = \begin{cases} IC_i : g = 1 \\ IC_{gi} : g < 1 \end{cases}$ with $IC_i, IC_{gi} \in \mathbb{R}^+$ and $IC_i < IC_{gi}$. Thereby, $g < 1$ implies that not all members of the ITIP work in the same geographical location and can therefore be seen as a virtual team. Consequently, a more expensive IT platform with corresponding equipment for an extended range of functions (e.g. for video conferences, collaborative working, shared data access) as well as the associated workplace equipment is needed if personal meetings of the team members are not feasible. A sophisticated IT platform is further important to overcome struggles in virtual team's cohesion as good as possible (Salisbury et al. 2006). Vice versa, $g = 1$ implies that only an essential IT platform (e.g. mail support) is needed since local meetings replace virtual collaboration. Therefore, the project initiation costs IC_{gi} for establishing an IT platform that enables collaboration between different geographical locations are assumed to be higher than the initiation costs IC_i for an IT platform that is needed in case of only local collaboration.

Summarizing, the total costs $TC_{ITIP}(RC, IC)$ of the ITIP are: $TC_{ITIP}(RC, IC) = RC(P, w_m) + IC(g)$

Assumption 5 - Benefits: The focus of the extensive literature on team design and performance is predominantly on the input variables but not on the output variable – the team performance (Ilgen, 1999). Unfortunately, it is difficult to generalize performance, as it is context specific. In our case, we - in accordance with IT innovation literature - distinguish the two following benefit factors to measure the performance of the ITIP (Reichwald and Piller, 2009):

A) Fit-to-market: The benefit factor fit-to-market FTM $\in \mathbb{R}^+$ measures the degree to which the result of the ITIP meets the customers' and market's needs. The higher FTM, the higher the customer's willingness to pay and thus the greater the economic potential of the ITIP's outcome.

B) New-to-market: The benefit factor new-to-market NTM $\in \mathbb{R}^+$ measures the IT innovation's degree of novelty perceived by potential customers. The higher NTM - i.e. the more revolutionary the IT innovation - the higher the chance to attract the customer’s attention and to gain a unique selling proposition.

We assume that a previous reference project (cf. assumption 6) has a NTM and FTM equal to one. Depending on its specific design, the NTM and FTM of the considered ITIP might deviate from one. For example, a NTM of two means that the innovation is twice as good as the reference project’s innovation with regard to the factor new-to-market. Thereby, the ITIP’s values of NTM and FTM depend on the concrete manifestation of the considered influencing factors (e.g. team size). However, as there is a clear distinction between the definitions of both factors in scientific literature (Reichwald and Piller 2009), we do not consider dependencies between both factors. Furthermore, to examine the company’s individual effort, objectives, and business environment, we use the factor $\propto \epsilon [-1,1]$ in order to express which of the two factors contributes more strongly to the overall performance. Thereby, $\propto = 0$ implies that both factors equally influence the overall performance. Furthermore, $\propto = 1$ respectively $\propto = -1$ imply that only the factor NTM respectively FTM influence the performance. However, such extreme values are unlikely to occur in reality, as the other factor would not have any influence at all. Therefore, values are supposed to lie in the interval $(-1; 1)$ and have to be determined by expert’s assessments. For example, if the company’s primary objective is to gain a unique selling proposition by generating innovations with a high degree of novelty, the factor NTM would have a higher relevance than the factor FTM which would imply $\propto > 0$.

Assumption 6 - Reference project: The objective function (cf. assumption 11) weighs up benefits and costs that result from a certain manifestation of the ITIP’s team design. However, we assume that the innovation team is stronger involved in the earliest stage of the innovation process. Therefore, it is only possible to determine the costs of an ITIP directly but not the prospective revenue of the generated innovation which is realized in the commercialization phase. Therefore, we need a proxy to draw conclusions about the prospective ITIP’s revenue. This proxy is a previous reference project that represents an IT innovation project carried out by the company’s R&D department. To illustrate the basic idea: if the ITIP’s team design leads to a FTM and NTM >1 (and therefore a higher FTM and NTM than the reference project with $FTM = NTM = 1$), we also expect a higher revenue than the reference project’s revenue. Therefore, in order to utilize this approach, we need the revenue $\mathrm{R_{RP}}$ and the relevant previously described parameters of a reference project$\mathrm{R_{RP}}$ $(\mathrm{P_{RP}}, \mathrm{w_{m_{RP}}}, \mathrm{w_{d_{RP}}}, \mathrm{a_{RP}}, \mathrm{g_{RP}})$. If, for example, the ITIP’s team size is higher than the ones in the reference project, we expect a higher ITIP’s NTM (i.e.,$\mathrm{NTM} > 1$) and thus a higher ITIP’s revenue. The effects of the particular parameters on the factors FTM and NTM will be described in the following. Figure III.1-1 demonstrates the approach.

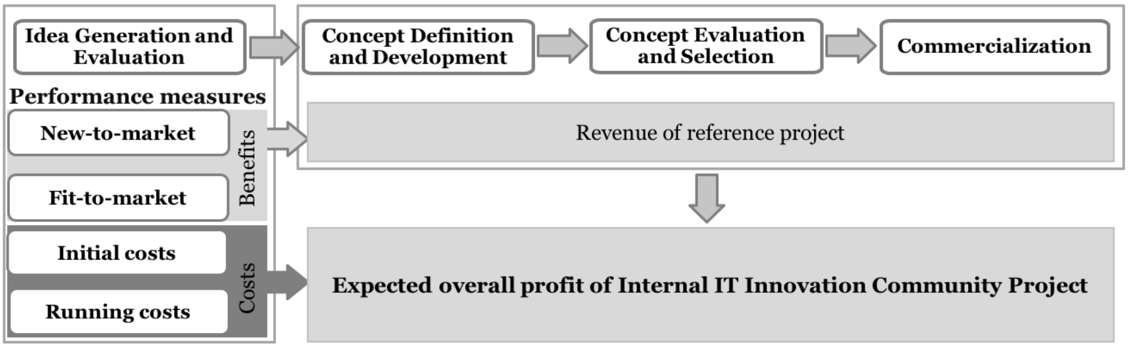

Figure III.1-1 Reference project approach to measure overall profit

Assumption 7 - The influence of the team size on new-to-market: The degree of NTM depends on the team size $\mathrm{P} \in \{2,3,..,\mathrm{n}\}$ and follows a function in the form of an s-curve: $\mathrm{NTM_P(P)} = \mathrm{G_P} * \left(1 + \mathrm{e}^{\mathrm{k_P}(\mathrm{b_p}-\mathrm{P})}\right)^{-1}$ with $\mathrm{NTM_P(P)} \in \mathbb{R}^+$. Thereby, $\mathrm{b_p} \in \mathbb{R}^+$ describes the s-curve's turning point, $\mathrm{k_P} \in \mathbb{R}^+$ the gradient of increase at the s-curve's turning point and $\mathrm{G_p} \geq 1$ the s-curve's upper limit. We assume $\mathrm{b_p} = \mathrm{P_{RP}} + \ln(\mathrm{G_P} - 1) * \mathrm{k_p^{-1}}$, as the same number of team members in the ITIP as in the reference project should both result in $\mathrm{NTM_P} = 1$. Furthermore, $\mathrm{G_p}$ represents the degree to which $\mathrm{NTM_P}$ is limited. For example, $\mathrm{G_p} = 2$ implies that the ITIP's $\mathrm{NTM_P}$ can only be twice as high as the reference project's $\mathrm{NTM_P}$. Figure III.1-2 illustrates two exemplary s-curves for a reference project with $\mathrm{P_{RP}} = 6$.

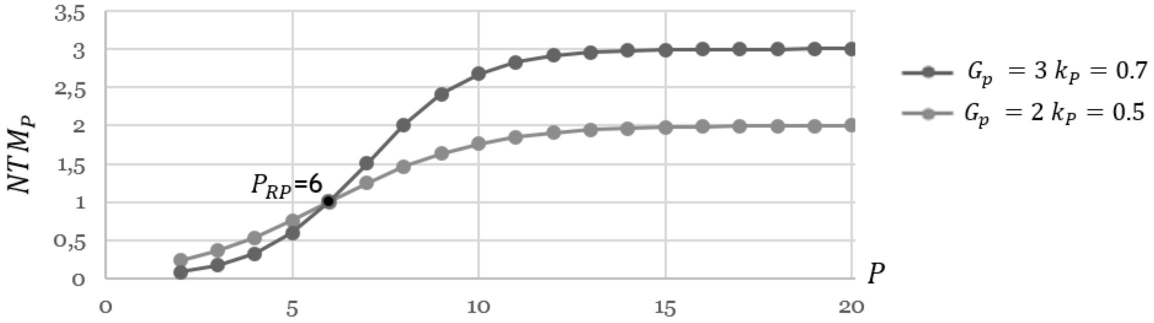

Figure III.1-2 Exemplary s-curves for the influence of the team size on the NTM factor

A positive relationship between the parameters P and NTM is reasonable, as with every additional team member, the chances of generating a revolutionary idea increase. Although there is no general agreement in literature on optimal team size, most studies agree that there is an optimal range. For example, the Scrum framework (Sutherland and Schwaber 2013) mentions a preferred team size between three and nine people. Nevertheless, also very large teams still show increasing benefits as demonstrated by Bonabeau (2009) and Fay et al.

(2006). Although every additional team member still increases the absolute benefit, the marginal benefit decreases as the incorporation of a new team member is less useful in large teams. The 20th team member in a team for example obviously does not add as much value as the 5th one did. Thus, the form of an s-curve is reasonable. The team size only influences the benefit factor NTM since the pure number of people contributes to a wider range of perspectives and ideas but not to a better market assessment.

Assumption 8 - The influence of work experience on new- and fit-to-market: The team's mean work experience $\mathrm{w_m}$ and the team's work experience diversity $\mathrm{w_d}$ result in different effects:

A) Mean work experience: The degree of FTM depends on the team's mean work experience $\mathrm{w_m} \epsilon \, \mathbb{R}^+$ and follows an s-curve: $\mathrm{FTM_{w_m}(w_m) = G_{w_m} * \left(1 + e^{k_{w_m}(b_{w_m} - w_m)}\right)^{-1}}$ with $\mathrm{FTM_{w_m}(w_m)} \epsilon \, \mathbb{R}^+$. Thereby, $\mathrm{G_{w_m}, b_{w_m}}$ and $\mathrm{k_{w_m}}$ as well as the s-curve effect can be interpreted analogously to assumption 7. The assumed influence of $\mathrm{w_m}$ on FTM is plausible as a higher mean work experience results in higher skills to address issues that are critical to success (e.g., market perspective and assessment of customer demands). However, the marginal benefit decreases as the relevance of an even higher work experience is less substantial in already highly experienced teams. Moreover, $\mathrm{w_m}$ has no influence on NTM as a team with a high mean work experience is not necessarily more creative or more innovative.

B) Work experience diversity: The degree of NTM depends on the team's work experience diversity $\mathrm{w_d} \epsilon \, \mathbb{R}^+$ and follows an s-curve: $\mathrm{NTM_{w_d}(w_d) = G_{w_d} * \left(1 + e^{k_{w_d}\left(b_{w_d} - w_d\right)}\right)^{-1}}$ with $\mathrm{NTM_{w_d}(w_d)} \,\epsilon\, \mathbb{R}^+$. Thereby, $\mathrm{G_{w_d}, b_{w_d}}$ and $\mathrm{k_{w_d}}$ as well as the s-curve effect can be interpreted analogously to assumption 7. The assumed positive relationship between $\mathrm{w_d}$ and NTM is reasonable as a higher number of differently experienced team members contributes to more different perspectives and more creative ideas. This relationship is supported by various studies that found that a team's informational diversity (defined as the diversity resulting from deviations in someone's knowledge and experience) often increases creativity (Albrecht and Hall 1991; Payne 1990). However, the marginal benefit decreases as the relevance of a higher work experience diversity is less substantial in already highly diversified teams. Moreover, $\mathrm{w_d}$ has no influence on FTM as work experience diversity does not contribute to a better market assessment.

Assumption 9 - The influence of geographical diversity on fit-to-market: The degree of FTM depends on the team's geographical diversity $\mathrm{g} \,\epsilon\, (0,1]$ and follows an s-curve: $\mathrm{FTM_g(g)} =$

$\mathrm{G_g} * \left(1 + \mathrm{e}^{\mathrm{k_g}(\mathrm{b_g}-\mathrm{g})}\right)^{-1}$ with $\mathrm{FTM_g(g)} \in \mathbb{R}^+$. An increasing g implies a decreasing degree of geographical diversity. Thereby, $\mathrm{G_g}, \mathrm{b_g}$ and $\mathrm{k_g}$ as well as the s-curve effect can be interpreted analogously to assumption 7. However, $\mathrm{k_g} \in \mathbb{R}$ may take negative values in order to reflect the company's goals with regard to the geographical distribution of the innovation. The assumed relation between g and FTM is reasonable, as a higher geographical diversity results in better market assessment skills that are critical to success (e.g. in-depth knowledge regarding regional customer preferences) and allows to generate, import, share, interpret and apply market knowledge, particularly of local markets (Gibson and Gibbs 2006). Especially in case the company aims to distribute the innovation globally, an accurate market assessment of the different regions is essential, which is reflected by a negative gradient $\mathrm{k_g} < 0$ (leading to a horizontally mirrored s-curve). We assume globally distributed innovations to be used in a product-oriented manner. Vice versa, if the company aims to distribute the innovation only regionally, a high geographical diversity even could have counterproductive effects. This scenario can be reflected by a positive gradient $\mathrm{k_g} > 0$. However, analogous to the other s-curves, the marginal benefit decreases with an increase (or decrease - depending on the scenario) of geographical diversity, as the relevance of another geographical location is less substantial in already highly geographically diversified ITIPs. Moreover, the geographical diversity does not necessarily stimulate creativity and innovation and, therefore, does not affect the benefit factor NTM.

Assumption 10 - The influence of academic background diversity on new-to-market: The degree of NTM depends on the team's academic background diversity $\mathrm{a} \in (0,1]$ and follows an inverse u-curve: $\mathrm{NTM_a(a)} = (1 - \mathrm{G_a}) * (\mathrm{b_a} - \mathrm{k_a})^{-2} * (\mathrm{a} - \mathrm{b_a})^2 + \mathrm{G_a}$with$\mathrm{NTM_a(a)} \in \mathbb{R}^+$. Thereby, $\mathrm{k_a} \in [0; 1]$ and $\mathrm{G_a} \geq 1$, determine the u-curve's vertex at $(\mathrm{k_a}|\mathrm{G_a})$ and therefore the point until which the marginal utility of $\mathrm{NTM_a(a_{RP})}$ increases with an increasing a and vice versa. Furthermore, we assume $\mathrm{b_a} = \mathrm{a_{RP}}$, due to $\mathrm{NTM_a(a_{RP})} = 1$. The modelled inverse u-curve is reasonable for several reasons: First, task-related diversity, such as dissimilarity in education, was found to significantly improve team performance, especially in highly complex and uncertain tasks (Horwitz and Horwitz 2007; Van de Ven and Ferry 1980). Second, analogous to the work experience diversity, informational diversity stimulates creativity and innovation in teamwork (Albrecht and Hall, 1991; Payne, 1990). Third, there is a point of 'too much diversity' from where on team members would not be able to share and align their ideas efficiently due to extensive debates, rising coordination efforts, and increasing difficulties in establishing a common problem understanding. Therefore, a highly heterogeneous group with regard to academic background is supposed to be rather counterproductive (Jehn et al. 1999; Jehn et al. 1997). The parameter academic background diversity only influences NTM, as it involves the variety of different skills that stimulate revolutionary ideas. In contrast, the academic background diversity is not related to a better market assessment, which is primarily driven by the work experience of the team members. Figure III.1-3 summarizes the assumptions, parameters and their impact on the benefits and costs.

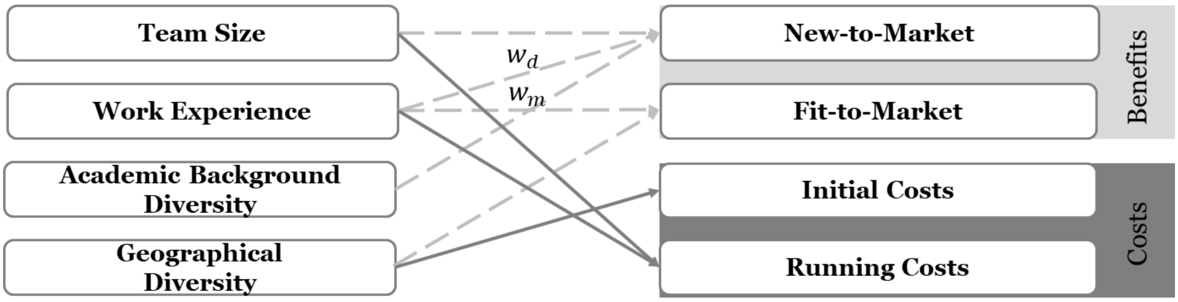

Figure III.1-3 Relevant parameters and their relationships to benefits and costs

Assumption 11 - Overall objective function: To determine the profit P_{ITIP} of an ITIP, we subtract the total costs TC_{ITIP} from the estimated revenue R_{ITIP}, which is determined with the help of the reference project's revenue R_{RP} (cf. assumption 6). In order to determine the highest possible profit, we maximize the following objective function subject to the outlined parameters.

$$\max_{\mathbf{P},\mathbf{w_d},\mathbf{w_m},\mathbf{a},\mathbf{g}} \mathbf{P_{ITIP}} = [\mathbf{R_{ITIP}} - \mathbf{TC_{ITIP}}]$$

$$\mathrm{s.t.}\, R_{ITIP} = R_{RP} * (1 + (\Delta R_{NTM_P} + \Delta R_{NTM_{w_d}} + \Delta R_{NTM_a}) + (\Delta R_{FTM_{w_m}} + \Delta R_{FTM_g}))$$

$$\Delta R_{NTM_n} = (1+\propto) NTM_n(n_{ITIP}) - 1 \qquad \Delta R_{FTM_f} = (1-\propto) FTM_f(f_{ITIP}) - 1$$

$$n \in \{P, w_d, a\} \; \forall \, f \in \{w_m, g\}$$

Thereby, ΔR_{NTM_n} and ΔR_{FTM_f} represent the absolute change in the benefit factors weighted at their specific influence $\propto$, e.g. $\Delta R_{NTM_P} = (1+\propto) NTM_P(P_{ITIP}) - 1$. Table III.1-1 summarizes the major parameters of the model.

Parameter	**Description**	**Parameter**	**Description**
Parameters (for reference project RP *and innovation project* ITIP*)*		*Objective Function*	
P	Team size / number of team members	R_{RP}	Revenue of reference project
w_m	The team's mean work experience	R_{ITIP}	Revenue of ITIP
w_d	The team's work experience diversity	TC_{ITIP}	Total Costs of ITIP
a	The team's academic background diversity	P_{ITIP}	Profit of ITIP
g	The team's geographical background diversity	$\propto$	Weighting factor for FTM_f and NTM_n
Costs of ITIP		*Benefits*	
$RC(P, w_m)$	Total running costs	FTM_f	Fit-to-Market with $f \in \{w_m, g\}$
$IC(g)$	Total initial costs	NTM_n	New-to-Market with $n \in \{P, w_d, a\}$
Company specific parameters to determine costs		*Parameters for* $\mathrm{FTM_f}$ *and* $\mathrm{NTM_n}$ *s- and u-curves with* $\mathrm{n} \in \{\mathrm{P}, \mathrm{w_d}, \mathrm{a}\} \forall \mathrm{f} \in \{\mathrm{w_m}, g\}$	
RC_{P_i}	Company’s individual personnel expenses	G	Global curve’s upper limit
IC_i	Company's initial costs to run an ITIP at one location	k	Gradient of increase at the curve’s turning point / point of vertex
IC_{gi}	Company's initial costs to run a geographical diversified ITIP (e.g. for IT platforms)	b	S-curve’s turning point
S_i	Company's individual salary structure		

Table III.1-1 Summary of major Parameters

III.1.3.3 Practical Substantiation of Model Assumptions

To provide not only scientific but also practical evidence for the model assumptions, we interviewed two practical experts. Thereby, both experts hold senior management positions and are conversant with designing project teams. The first interview partner works for a large German industry company – a manufacturer of optical systems and industrial measurement, the second one for a small start-up company in the financial services industry. In the following, Table III.1-2 presents the substantiation of our model assumptions. Controversial statements, or those in which the two experts contradict each other, are subsequently discussed with reference to our model.

Expert 1: Large industry company	Expert 2: Small start-up for financial services
Assumption 1 - Relevant ITIP team design parameters	
• The considered team design parameters are relevant in practice. • A further parameter could be individual soft skill level, since the quality of communication and collaboration in the team can have a significant influence on the team performance. Thereby, a balance between a purely homogeneous (i.e. exclusively structured team members) and heterogeneous team must be found. However, the parametrization of the variable soft skill level is considerably difficult (see subsequent discussion). • Additionally, the working environment like (IT) infrastructure, tools and managerial attention may have a significant influence on team performance (see subsequent discussion).	• The considered team design parameters are relevant in practice. • Geographical diversity is only relevant if a company is distributing its IT innovations globally. However, if so, geographical diversity is highly important (included in our model). • A further parameter could be individual soft skill level, especially if the team size is relatively low. However, at least a minimum soft skill level should by fulfilled. If this assumption is fulfilled, the team design will be aligned on the team design parameters that are contained in our model. This is due to the fact that a highly destructive team member might have a highly negative impact on the whole team (see subsequent discussion). • Another important parameter could be the leadership skill level. Thereby, at least one team member should obtain a high leadership skill level (partly included in our model via work experience).
Assumption 2-4 - Costs of an ITIP & cause-effect-relationships on costs	
• The considered cost drivers are relevant in practice. • Furthermore, the running costs after the new product or service launch, e.g. maintenance service, may be considered (see subsequent discussion).	• The considered cost drivers are relevant in practice. • Main cost drivers to run a geographically diversified team are the expenditures to equip the different workspaces, if not available yet (included in our model). • Running costs for a geographically diversified team are heavily depending on the respective project since regular

	physical coordination appointments might be necessary (included in our model via value of RC_{P_i}). • Depending on the salary structure in the company, the work experience may have a significant impact on the running costs (included in our model via value of S_i). • The team size may also lead to initial costs since further investments in equipment might be necessary depending on the available equipment (included in our model via value of IC_{gi}).
Assumption 5 - Benefits	
• The assumption is meaningful. • The number of generated ideas and the time-to-market might be considered as further benefits (see subsequent discussion). • The risk aspect of a high NTM strategy might be considered (see subsequent discussion).	• The assumption is meaningful. • The number of generated ideas and the time-to-market might be considered as further benefits (see subsequent discussion).
Assumption 6-10 - Cause-effect-relationships on benefits	
• The assumptions are basically meaningful and recognizable in practice. • The academic background diversity may have an impact on the ITIP costs, since it may take longer to reach a common understanding (can be considered in our model by an appropriate parameterization of assumption 10). • The geographical diversity may have an impact on the ITIP costs due to a different regional salary structure as well as intercultural costs for communication due to linguistic difficulties (see subsequent discussion). • Depending on the idea to be brought out, the academic background diversity might have the highest influence on NTM (can be considered in our model by an appropriate parameterization of assumption 10). • A (too) large number of team members has a much more negative effect than a (too) small number of team members due to the associated	• The assumptions are basically meaningful and recognizable in practice. • The academic background diversity may also have an impact on FTM since there is a high chance that an innovation will meet the customers' and market's needs if it meets the needs of a heterogeneous team (provided that the team size is sufficiently large) (see subsequent discussion).

communication and coordination costs (can be considered in our model by an appropriate parameterization of assumption 7).	

Table III.1-2 Practical Substantiation for Model Assumptions

Based on the practical substantiation, we can state that our model generally reflects the occurring trade-offs and cause-effect-relationships in team design in practice. Of course, at some points we needed to make simplifications in order to increase the readability and understandability of the model and its results. Although both experts mentioned the soft skill level as an additional decisive parameter, we decided not to integrate this parameter in our model due to a considerably difficult measurement and parametrization of this parameter. With regard to mentioned potential parameter working environment, we assume in our model (Assumption 2 - Initial costs) that the project team is equipped with state-of-the-art (IT) equipment. A further improvement of this would have only a marginal positive effect. The quantity of generated ideas and the time-to-market play an important but subordinate role with regard to the factors integrated in the existing model. However, implementing these factors would be the next step in extending our simplified model as further discussed in the last Section of this paper. Additionally, further company- and project-specific contradicting statements can be incorporated in the model (i.e. by modifying model parameters) in the next step as also discussed in our practical model evaluation and proposed in the Section ‘Implications, Limitations and Outlook’.

III.1.4 Model Evaluation

In this Section, we demonstrate the functionality of our model and analyse the causal relationships between the influencing factors and associated effects on benefits and costs. Due to missing real-world data, we first choose one realistic initial scenario for a company that conducts an ITIP as a traditional R&D project (reference project). Based on the initial setting, we solve the model by determining an economically optimal team design for the ITIP. In the next step, we perform univariate sensitivity analyses for selected team design parameters. Subsequently, to examine the effect of random team designs in contrast to a well-founded one, we conduct a multivariate sensitivity analysis. Conclusively to underpin our model with a real-world case, we apply our model on the initial mentioned small start-up company in financial services industry.

Table III.1-3 shows the relevant parameter values for our initial scenario. For the reference project, we assume an ITIP undertaken by a traditional R&D team (6 team members, a mean work experience of 20 years and standard deviation of 5, an almost identical academic background, and all team members located at one subsidiary). Furthermore, we assume that the factor NTM is more important than the factor FTM ($\propto = 0.2$), which implies that the company's goal lies rather in gaining a unique selling proposition by generating an innovation with a high degree of novelty.

Parameters for reference project RP				*Parameters for* $\mathrm{FTM_f}$ *and* $\mathrm{NTM_n}$ *with* $\mathrm{n} \in \{\mathrm{P}, \mathrm{w_d}, \mathrm{a}\}\ \forall\ \mathrm{f} \in \{\mathrm{w_m}, g\}$			
$\mathrm{P_{RP}}$	6	$\mathrm{a_{RP}}$	0.9	G	2		
$\mathrm{w_{m_{RP}}}$	20	$\mathrm{g_{RP}}$	1	k	0.5 for $\mathrm{k_P}, \mathrm{k_{w_d}}, \mathrm{k_{w_m}}, \mathrm{k_a}$ and -5		
$\mathrm{w_{d_{RP}}}$	5			b	b is equal to particular parameter		
Company-specific parameters to determine costs				*Objective Function*			
$\mathrm{RC_{P_i}}$ $\mathrm{IC_i}$	\$ 100 \$ 500	$\mathrm{IC_{gi}}$ $\mathrm{S_i}$	\$ 1,000 0.2	$\mathrm{R_{RP}}$	\$ 1000	$\propto$	0.2

Table III.1-3 Parameter setting for the initial scenario

III.1.4.1 Ex-ante analysis of the optimal design of an ITIP

Based on the initial scenario (see Table III.1-3), we in the first step maximize the objective function to determine the theoretically optimal team design for an ITIP. These results build the base for further analyses. Table III.1-4 shows the optimal parameter values and the related profit. For our analysis, we limited the team's work experience diversity $\mathrm{w_d} \in \mathbb{R}^+$ to 25 to avoid an infinite number of possible project settings and then, an infinite number of optimal designs. This procedure coincides with a real-world scenario since the number of possible ITIP team designs is anyway limited due to the characteristics of the potential team members. Therefore, a company would rather calculate the profit for a limited number of feasible designs than to determine one theoretically optimal design – which might not be realizable at all due to the limited number of possible team members.

Theoretical economically optimal design of ITIP team				
$\mathrm{P_{ITIP}}$	$\mathrm{w_{m_{ITIP}}}$	$\mathrm{w_{d_{ITIP}}}$	$\mathrm{a_{ITIP}}$	$\mathrm{g_{ITIP}}$
9	28.3	25	0.5	0
Related revenue, costs, and profit of ITIP				
$\mathrm{R_{ITIP}}$	$\mathrm{RC_{ITIP}}$	$\mathrm{IC_{ITIP}}$	$\mathrm{TC_{ITIP}}$	Profit
\$ 5,726.12	\$ 1,755.89	\$ 1,000.00	\$ 2,755.89	\$ 2,970.23

Table III.1-4 Optimal team design and results of ITIP

Influence of the team size: Based on our initial scenario and its optimal parameterization (see Table III.1-3 and Table III.1-4), we calculated the ITIP profit for diverging numbers of team members $\mathrm{P}_{\mathrm{ITIP}}$ in a range of 2 to 40 people, assuming that all other parameters remain constant (see Figure III.1-4). Regarding the influence of the team size $\mathrm{P}_{\mathrm{ITIP}}$, we can conclude that, according to our model, an ITIP team should be formed of around 6 to 11 people regarding the optimal ITIP profit. That fits with previous research, which finds that larger teams (i.e., more than 5 team members) develop more radical innovations (West and Anderson, 1996). In case of scenarios with a low number of team members ($\mathrm{P}_{\mathrm{ITIP}} \leq 4$), we can even observe decreasing profits with an increasing number of team members. This is due to the fact that the running costs $\mathrm{RC}_{\mathrm{ITIP}}$ increase more strongly than the additional revenue $\mathrm{R}_{\mathrm{ITIP}}$ resulting from a higher $\mathrm{NTM}_{\mathrm{P}}$. Teams of 5-8 people show an increasing profit with a growing number of team members, since the revenue $\mathrm{R}_{\mathrm{ITIP}}$ arising from a higher $\mathrm{NTM}_{\mathrm{P}}$ increases more strongly than the running costs $\mathrm{RC}_{\mathrm{ITIP}}$. In case of team sizes larger than 8 persons, a further increase in team members will result in decreasing profits as the additional running costs $\mathrm{RC}_{\mathrm{ITIP}}$ overcompensate the increase in revenue $\mathrm{R}_{\mathrm{ITIP}}$.The profit will be even negative for a high number of team members ($\mathrm{P}_{\mathrm{ITIP}} \geq 27$) since the high running costs $\mathrm{RC}_{\mathrm{ITIP}}$ exceed the revenue $\mathrm{R}_{\mathrm{ITIP}}$.

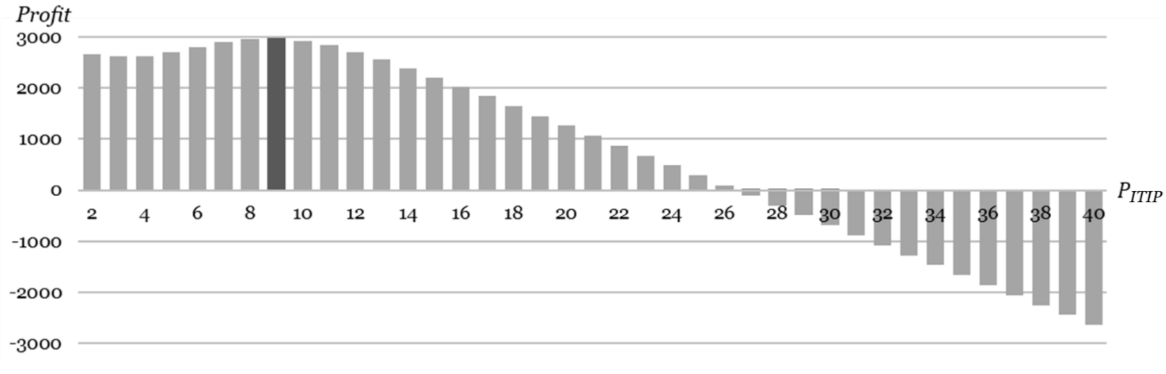

Figure III.1-4 Univariate sensitivity analysis for $\boldsymbol{P_{ITIP}}$

Influence of the mean work experience: In the next step, we calculated the ITIP profit for a mean work experience $\mathrm{w}_{\mathrm{m}_{\mathrm{ITIP}}}$ in a range of 0 to 40, assuming that all other parameters remain constant (see Figure III.1-5). Regarding the influence of the team's mean work experience $\mathrm{w}_{\mathrm{m}_{\mathrm{ITIP}}}$, we can conclude that an ITIP team should have a high mean work experience, optimally in the range of 22 to 30 years, to be able to realize the maximal ITIP profit. If we assume that the team members start gathering their work experience at the age of 18, this will imply an optimal mean participant's age in the range of 40 to 58 years. In cases of a low mean work experience (up to 11 years), we can observe decreasing profits with an increasing mean work experience. The reason for that is, that with an increasing mean work experience, the running costs RC_{ITIP} increase more strongly than the revenue R_{ITIP} resulting from a higher FTM_{w_m} until a point of inflection ($w_{m_{ITIP}}$=12). Then, with an increasing marginal benefit, we can observe a positive relationship between the mean work experience and the ITIP profit until a second point of inflection - the optimal parameterization ($w_{m_{ITIP}}$=28.3) - as the revenue R_{ITIP} increases more strongly than the running costs RC_{ITIP}. In cases of a higher mean work experience, the profit decreases due to the decreasing marginal benefit of $w_{m_{ITIP}}$. Therefore, we can observe a negative relationship since the increased revenue R_{ITIP} is overcompensated by higher running costs RC_{ITIP}. However, this decreasing profit is still higher than in cases of a low mean work experience.

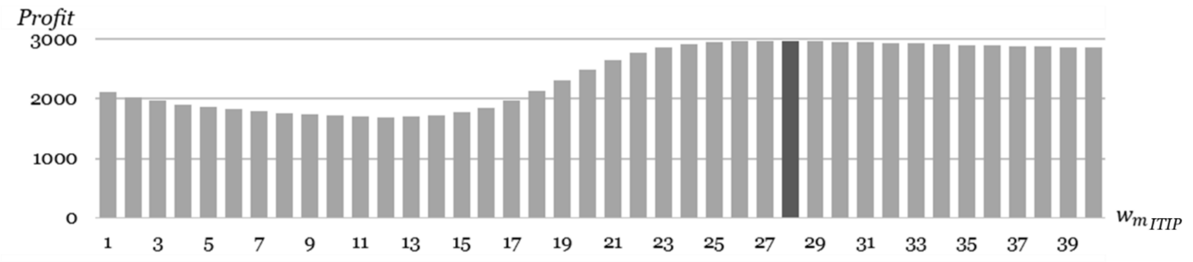

Figure III.1-5 Univariate sensitivity analysis for $w_{m_{IITP}}$

Influence of the work experience diversity: We further calculated the ITIP profit for a work experience diversity $w_{d_{ITIP}}$ in a range of 0 to 25, assuming that all other parameters remain constant (see Figure III.1-6). Based on the sensitivity analysis, we can state that there is a generally positive relationship between the work experience diversity $w_{d_{ITIP}}$ and the ITIP profit. This is because in our model, work experience diversity $w_{d_{ITIP}}$ has only a positive influence on the profit and is not related to any costs. Furthermore, we can conclude that the team members in an ITIP should be highly diversified in terms of their work experience. However, the marginal benefit is relatively low in cases of an already high work experience diversity. Therefore, companies should staff an ITIP team with heterogeneous team members in terms of their work experience to achieve an optimal profit, whereas an extraordinary high diversity is not necessary due to the observable point of saturation ($w_{d_{ITIP}}$values higher than approximately 13). That fits the results of previous research, which states that cognitive team diversity has a positive influence on team performance as it promotes creativity, innovation and problem solving (Cox and Blake 1991; Hambrick et al. 1996). In this view, cognitive diversity is defined as the degree to which the team members differ in terms of expertise and experiences, a definition that is very well applicable in our context. The positive effect of a higher work experience diversity results in an increased $\text{NTM}_{\text{w}_\text{d}}$ that, in turn, leads to a higher R_{ITIP} and a higher profit.

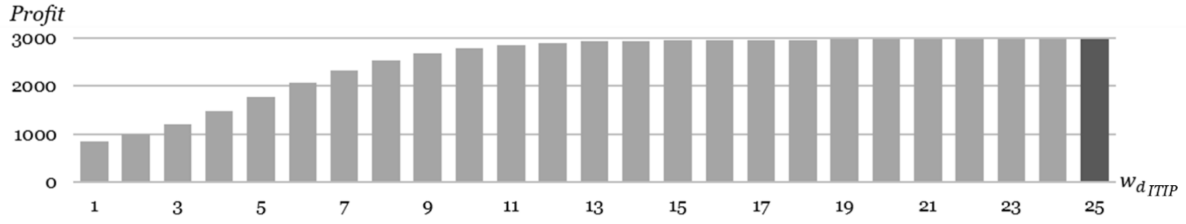

Figure III.1-6 Univariate sensitivity analysis for $\boldsymbol{w_{d_{ITIP}}}$

Influence of the academic background diversity: Analogous to the previous analyses, we calculated the ITIP profit for an academic background diversity a_{ITIP} in a range of 0 to 1, assuming that all other parameters remain constant (see Figure III.1-7). Regarding the influence of the team's academic background diversity a_{ITIP}, we can conclude that an ITIP team should be neither extremely heterogeneous nor homogeneous in order to achieve an optimal ITIP profit. This finding underlines former research, which emphasizes that academic background diversity is more likely to lead to improved performance when tasks are non-routine. However, extreme differences in academic background lead to an increase in task-related, time-consuming debates and are therefore rather counterproductive (Jehn et al. 1999; Jehn et al. 1997). Unsurprisingly, an appropriate mix of academic background will lead to a higher NTM_a and consequently to a higher R_{ITIP} and profit, as the academic background diversity is not related to any costs.

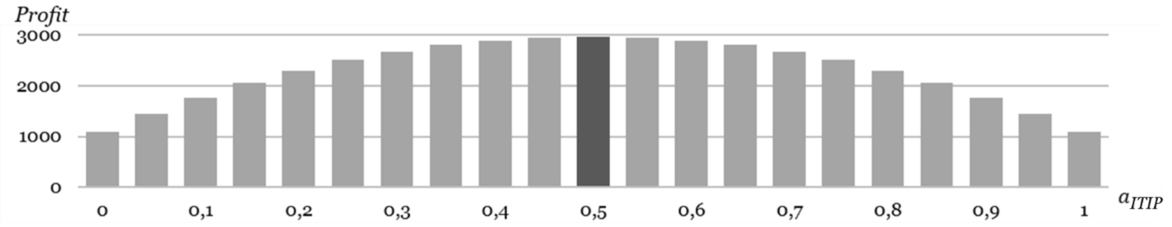

Figure III.1-7 Univariate sensitivity analysis for a_{ITIP}

Influence of the geographical diversity: Finally, we calculated the ITIP profit for a geographical diversity g_{ITIP} in a range of 0 to 1, assuming that all other parameters remain constant (see Figure III.1-8). As a result, we can observe that an increasing geographical diversity leads to a higher ITIP profit (for cases if $\text{g}_{\text{ITIP}} < 1$). This effect is a consequence of a higher FTM_g and hence, a higher R_{ITIP} and profit, as the geographical diversity is not related to running costs. However, since g_{ITIP} is related to the initial costs IC_i and IC_{gi}, we can also state that an ITIP that is located at only one place leads to a higher profit than an ITIP with a very low geographical diversity (due to the lower initial costs IC_i). However, this effect is highly dependent on the initial costs. For example, if $\mathrm{IC_i} = \mathrm{IC_{gi}}$ (what would be the case, if the company has already a sufficient communication platform), the entire histogram would show a negative relationship. This would imply that the higher the geographical diversity, the higher the profit. Vice versa, if $\mathrm{IC_{gi}}$ would be considerably higher than $\mathrm{IC_i}$ (what e.g. would be the case, if the company has not established any kind of communication platform yet and, thus, has high initial implementation costs), it would be advisable not to set up a geographically diversified ITIP. This result is in line with former research that states that the usage of IT platforms has a positive effect on the relationship between geographical diversification and project performance, as an IT platform is an enabler of project coordination and management across geographically diversified teams (Bardhan et al. 2013).

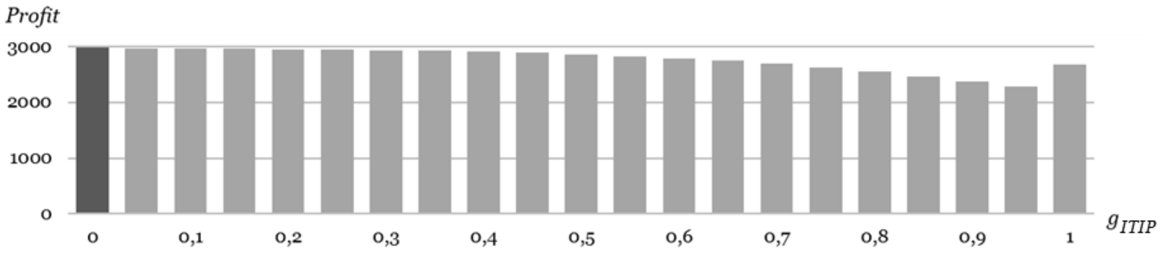

Figure III.1-8 Univariate sensitivity analysis for $\boldsymbol{g_{ITIP}}$

III.1.4.2 Multivariate sensitivity analysis

The multivariate sensitivity analysis aims to compare the profits of randomly chosen ITIP team design settings to the well-founded ones. Using this analysis, we generated 10,000 arbitrary chosen parameter settings for two scenarios, covering a broad range of possible ITIP settings. In contrast to the previous analyses, we now change all considered design parameters of an ITIP team simultaneously and calculate the profit for all ITIP settings. Table III.1-5 summarizes the ranges for both scenarios used for the simulation. Thereby, scenario 1 represents a case in which the ITIP team design is rather indiscriminate (e.g., wide ranges for team members, the academic background and geographical diversity). In contrast, scenario 2 represents a case in which the ITIP team design is rather thoughtfully since the parameter's ranges are based on the previous univariate sensitivity analyses. Through this analysis, we demonstrate to what extent a well-founded and value-oriented design of an ITIP team may outperform an arbitrary decision. We assume equal distributions for all parameters as other distributions (such as the Gaussian distribution) would not distort the general findings but would increase complexity.

Team Parameters	p_{ITIP}	$w_{m_{\mathrm{ITIP}}}$	$w_{d_{\mathrm{ITIP}}}$	a_{ITIP}	g_{ITIP}
Scenario 1	{2;3;…;40}	(0 ; 50)	$(0\ ;\frac{w_{m_{\mathrm{ITIP}}}}{2})$	(0 ; 1]	(0 ; 1]
Scenario 2	{6;7;…;11}	(20 ; 30)	$(0\ ;\frac{w_{m_{\mathrm{ITIP}}}}{2})$	(0.3 ; 0.8)	(0 ; 1]

Table III.1-5 Data for the multivariate sensitivity analysis

Using the histogram resulting from the multivariate sensitivity analysis (see Figure III.1-9), we illustrate the distribution of the ITIP profit for both scenarios. The histogram for scenario 1 shows that the ITIP profit covers a wide range between -$5,500 and $3,000. Thereby, a substantial number of projects (76%) leads to a negative profit. This supports the proposition that a random design of an ITIP as in scenario 1 most likely leads to a lower or even negative profit. Moreover, the 25% quantile (-$3,046) and the mean profit (-$1,541) support the need for a well-founded ITIP team design. In contrast, in scenario 2, the profit is positive in 95% of all cases. In addition, the 25% quantile ($680) and the mean profit ($1,383) support the statement that a well-founded design of an ITIP team has a much higher success potential than a random decision. The standard deviations for scenario 1 and 2 are $2,045.14 and $831.86, respectively. Thus, next to the risk of negative profits, the volatility of realized profits is considerably higher when relying on arbitrary ITIP team designs.

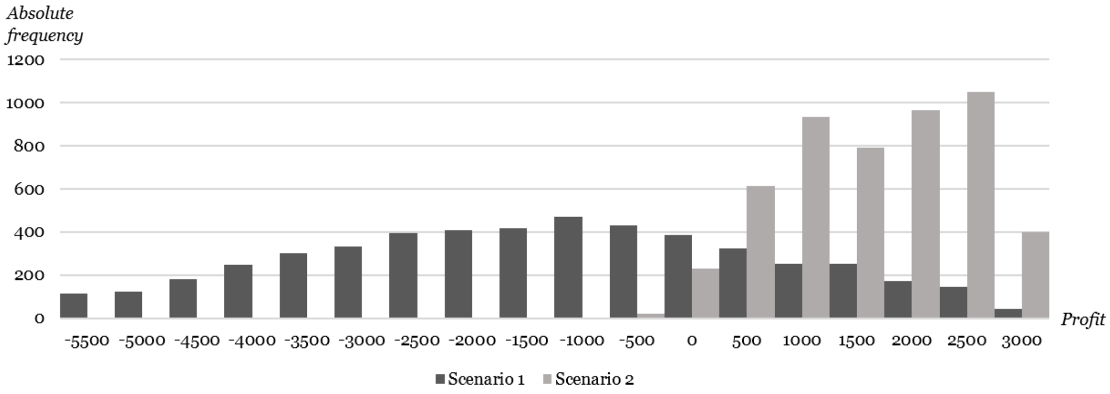

Figure III.1-9 Results for ITIP profit after multivariate sensitivity analysis

III.1.4.3 Practical Model Evaluation

To address the applicability of our approach in practice, we evaluated our model with our second interview partner – the expert working in a leading position at a small start-up company in the financial services industry. Analogously to the theoretical evaluation, we first determined the team design parameters for a typical innovation project of this company: 5 innovation team members, a mean work experience of 16 years and a standard deviation of 10.2 ($\vec{w}^{\mathrm{T}} = (5,15,15,25,35)$), as well as an almost identical academic background ($a_{\mathrm{ITIP}} =$

0.8). The low academic background diversity is reasonable since four of the innovation team members obtain almost identical backgrounds (financial services, however two of them with a sales focus and two with an IT focus) and only one a completely divergent (chemical engineer). Furthermore, all team members are located at one subsidiary (g_{ITIP} = 1). Additionally, the factor NTM is more important than the factor FTM ($\propto = 0.2$), since the company's goal lies rather in gaining a unique selling proposition by generating an innovative financial services product with a high degree of novelty. However, the company aims to distribute the innovation regionally. In consultation with the expert, several model parameters compared to the initial scenario as shown in Table III.1-3 have been changed ($G_a = 1$, $k_a = 0.6$, $b_{wm} = 5$, $b_g = 1$) due to the divergent requirements and aims of the company and its innovation team compared to the initial scenario.

Team Parameters	P_{ITIP}	$w_{m_{ITIP}}$	$w_{d_{ITIP}}$	a_{ITIP}	g_{ITIP}
Start-up company in financial services industry	5	16	10.2	0.8	1

Table III.1-6 Data for the practical model evaluation

Analogous to the previous model evaluation, based on our practical scenario and its optimal parameterization, we calculated the ITIP profit for diverging numbers of team members P_{ITIP} in a range of 2 to 15 people (since no more suitable people are available in the company), assuming that all other parameters remain constant. Subsequently we repeated this step for the other relevant team design parameters to determine the optimal team design in the present practical case. Our approach allows us to derive the following implications:

- An increase in the number of team members P_{ITIP} from 5 to 9 implies an increase in profit of 40%. The profit development depending on the team size is similar to the initial scenario (see Figure III.1-4).
- A decrease in a_{ITIP} to 0.6, which implies an increase of the academic background diversity, would imply an increase in profit of 38%. The profit development depended on the academic background diversity is similar to the initial scenario (see Figure III.1-7). A further decrease of the academic background diversity, would imply heavily negative impact on profit. This profit development is reasonable since a higher academic background diversity contributes to more different perspectives and more creative ideas which is especially important in the present, NTM orientated, case.
- A modification of the factor geographical diversity g_{ITIP}, which implies that not all team members work in the same geographical location, would have a highly negative

impact on the profit. This effect is reasonable since the company aims to distribute the innovation only regionally. Therefore, a high geographical diversity would have counterproductive – negative – effects on the profit.

- A change in the work experience (regardless if diversity or mean) would go along with only a low profit increase since both factors in the described initial scenario are almost optimal.

Based on our findings we can conclude that the present team design can be optimized in terms of the corresponding profit by increasing the number of team members which should exhibit a slightly differentiating academic background. On the other hand, a change in the factors geographical diversity as well as work experience can easily lead to a high decrease in profit. The findings of our approach go along with the expert's strategic considerations in terms of future team design to optimize the team performance.

III.1.5 Implications, Limitations and Outlook

Despite intensive investigations in last decades, the question on how to design a team to increase the profit of an ITIP remains widely unanswered. To contribute to the closure of this research gap, we provide an approach for an ex-ante economic evaluation of ITIPs related to a set of essential team design parameters. Therefore, we derive key team design parameters and model their impact on the profit of an ITIP. We theoretically evaluate our model by calculating the profit of an ITIP for initial values and performing a sensitivity analysis to analyse the cause-and-effect-relationships of our model. We also evaluate our model with two experts from practice to validate our assumptions and to illustrate its applicability in a real-life case.

With our approach, we contribute both to academic research as well as to practice. From an academic perspective, our work contributes to a broad range of research in the field of team design, team performance and IT innovation projects. Our theoretical model reveals first insights, how and to what extent various team designs might impact the economic success of ITIPs. We further demonstrate that it can be worthwhile to analyse ITIPs with respect to team design from an ex-ante perspective and not limiting it to ex-post reviews. Moreover, to consider idiosyncrasies of different ITIPs, the effects of team design activities should be measured and analysed on project level and not only be evaluated on an individual, team or company level. As our analysis shows, a well-designed team considering the ITIP characteristics can reduce the risk of negative profit that might occur in case of rather arbitrary decisions on team design. In addition, our approach supports a deeper understanding of influencing factors that determine the economically optimal team design. Due to our model, the economically optimal team design depends on employee-specific characteristics (e.g., work experience or academic background) and company-specific characteristics like company's objectives (e.g., gaining a unique selling proposition or ensuring the market share) in terms of project-specific characteristics (e.g., costs). Our approach further provides a supporting evidence of past findings based on economic evaluations and thus underpins outcomes of prior research. For example, we illustrate that too much diversity can be negative for the team performance, and consequently for economic performance, due to a disproportionate increase in costs that is in line with findings of past studies (Hoisl et al. 2017; Jehn et al. 1999; Jehn et al. 1997). Our analysis also shows that the team size is a crucial design parameter as deviations from the optimal solution will result in a considerably lower or even negative ITIP profit. This is in line with previous research, which finds that small teams lack the diversity needed for innovation and that large teams, in contrast, hamper effective interaction, information exchange, and participation due to a rising communication complexity between team members (West and Anderson 1996; Zenger and Lawrence 1989). Thus, our model provides the basis for further investigations by academics in the future as addressed below in this Section.

Practitioners can apply our approach as a first step to analyse team design parameters and their impact on the profit of ITIPs instead of designing teams on a gut feeling. Thereby, the model can be used for an evaluation as well as for a re-evaluation of running projects to fine-tune the project team design for example due to new circumstances, requirements or changes in the team. Practitioners can do this analogous to the real-life start-up case as described in Section 'Practical Model Evaluation' by estimating the model parameters summarized in Table III.1-6. For that, they can estimate and adjust the functions for modelled relationships according to their circumstances (e.g. the project revenue and costs, which can be achieved through a certain team design). Even though it might be challenging to operationalize the theoretically optimal team design determined by our model exactly in practice, practitioners can use it as an indicator or proxy for an appropriate team design in their ITIPs. It also can help to analyse how deviations from the theoretical optimum affect the resulting profit of the ITIPs to derive appropriate measures for improving the team design. Practitioners can further use our approach for internal stakeholders to persuade them about the validity of the proposed or followed team design decision. For that purpose, they can drive scenario analyses to illustrate the impact of employee-specific, company-specific and project-specific characteristics on the project profit. They can also conduct sensitivity analyses of selected model parameters to demonstrate the game changers in the ITIP and to underline their importance. Such insights can further be used to underpin the need of a steady improvement in a company's innovation project and team management approaches, for example, by providing measurement concepts for improving the innovation project profit through a mindful team design.

Since our model partially is based on findings outside the IT innovation management subject area, like social psychological research, and due to missing real-world data and some restrictive assumptions, our model cannot be directly transferred into practice yet and is associated with several limitations. Probably, the most important challenge for future operationalization is how to determine concrete procedures to quantify the model's input parameters and variables covering the benefit and cost effects. A company may consider assessments through experts or consultants based on experience from former investments, or by cross-company benchmark analyses within the market. These assessments might be also helpful if companies do not have former reference projects to derive the values for costs and revenues. Furthermore, simplifying assumptions made in this paper require further investigations. For example, the actual interpretation of the benefit factors NTM and FTM and their conversion into a monetary outcome are rather abstract and need further research. To consider the benefits in a more holistic way, benefit factors time-to-market and cost-to-market should be incorporated. Further, our model only partly considers the effects of a geographically diversified and globally distributed innovation. The expert of a small start-up company in financial services industry also mentioned that the project objectives and team management and leadership skills are both important factors in practice. Therefore, the leadership role as well as the team member's soft skill level have to be considered in further research. To fine-tune our model, further factors can be incorporated. For example, internal and external factors, like the company size, the risk attitude, and the business environment, should be regarded in future research to allow the application of our model for a concrete company. Differentiating between innovation laggards, opportunistic adopters and systematic innovators might provide a more detailed view onto the company's innovator profile and the complexity of the desired IT innovation.

Despite these limitations, our model delivers first insights into this less examined but highly relevant topic. Thus, our approach allows for further development and serves as a basis for future analytical as well as empirical research to contribute to the closure of the stated research gap.

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III.2 Research Paper 3: "Science Drives Practice – or Vice Versa? Technology Hype Development Analysis Based on Scientific and Industrial Research"

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Submitted to:	International Journal of Innovation and Sustainable Development

Abstract: *New and upcoming technologies are constantly shaping today's world and society in virtually every aspect. Researchers in the industrial and scientific sector are constantly working on developing these new technologies. On their journey to technical maturity, these technologies experience varying interests by industrial and scientific research. Thereby, the idea of cyclical development has prevailed in hype-cycle models that have become popular among practitioners, although the cyclical course has not yet been sufficiently empirically investigated. The main contribution of this paper is to identify the developmental path of technologies with regard to the typical hype cycle course and exploring the time lag between scientific and practice-oriented research. Collecting information about the devolvement of these technologies and analyzing them are essential but extremely time-consuming tasks. Therefore, we collect large amounts of paper and patent publication data on 15 technologies by a developed automated webscraper. By introducing suitable mathematical methods of analysis, the interest of the industrial and scientific research communities can be quantified and the accuracy of our developed hypothesis on which community is leading can be statistically tested.*

III.2.1 Introduction

The pervasive digitalization and ever shorter innovation cycles force organizations to continuously invest in the management of technologies to keep pace with competition and maintain sustainable long-term success (Kohli and Melville 2018; Lucas et al. 2013). However, although organizations invest on average four percent of total revenue in technology and innovation initiatives (PwC 2018), these investment strategies are often not based on economic well-founded evaluations and analyses, but rather on a gut feeling or herd behavior, as the market for IT innovations is characterized by intense competition, unclear impacts, and an environment influenced by the hype surrounding innovations and technologies.

To generate competitive advantages through such investments, an economically well-founded investment strategy is of decisive importance since timing and extent of investment amounts considerably determine the associated risk and return profile. Therefore, in a first step, it is indispensable to understand the development path of technologies. In this context, it is helpful to consider the concept of “hype cycles” by Gartner Inc. (e.g., Panetta 2017), according to which different stages of maturity characterize the uncertain development of an emerging IT innovation.

This concept has become popular among practitioners, although the cyclical course has not yet been sufficiently empirically investigated (Jarvenpaa and Makinen 2008). However, to support the early identification of technology hypes and the determination of a technology’s life-cycle-phase, a sound research basis would be desirable to support companies in their already complex investment decisions. Companies could obtain a better assessment of the development path of technologies and a sound evaluation basis for investment decisions, e.g., for the pre-selection of potential innovations. Although recent literature has attempted to investigate the typical development path of technologies and thus to reproduce the typical hype cycle course, new analysis methods, e.g., by considering the time lag between scientific and industrial research, may significantly improve existing approaches.

While high-tech companies are in the public eye, many scientific researchers doing the essential work necessary for these companies’ innovative products remain mostly out of sight, despite being well known among experts. Having the practitioners carrying out Research and Development (R&D) activities in tech companies on one side and the scientific researchers at research institutes on the other side, the imposing questions are: what are their dependencies, their relationships and whose interest is leading?

As the amount of information in science and IT field increases exponentially every year, data analysis about that information or extraction of, e.g., papers and patents become more difficult and time-consuming. Until now, there have been studies focusing on information analysis of mass data regarding technology devolvement (e.g., Kim et al., 2012; Kim et al., 2011; Dereli and Durmusoglu, 2009; Kim et al., 2008; Rann, 1998; John, 1995; Campbell, 1983). These studies focused mainly on information analysis and new opportunity discovery to derive future forecasting (decision support) systems. VantagePoint developed a text-mining tool for discovering knowledge in search results from patent and literature databases (VantagePoint, 2009). However, most of prior research focus on information analysis and mainly forecasting services, but the dependencies between scientific and industrial research remain unobserved. Since this relationship plays an essential role in the early recognition of trends and determining the phase of technologies in their life cycle, this paper aims to shed light on these relationships and the role of the stakeholders in developing the innovations shaping our society and answer the following research questions:

RQ1: *Is the interest of scientific or industrial researchers leading in researching technologies?*

RQ2: *How can the developmental path of technologies be determined based on the interaction between scientific and industrial research?*

The main contribution of this paper is to identify the developmental path of technologies with regard to the typical hype cycle course and exploring the time lag between scientific and practice-oriented research. For this purpose, R&D activities by practitioners in the industry are compared to research work carried out by research institutes by collecting data about corresponding patents and papers for 15 technologies. The imposing question in this setting is the quest for possible correlations and causalities between industrial and scientific research.

The remainder of this paper is organized as follows. Following a discussion of the relevant literature in Section III.2.2, Section III.2.3 describes our methodology, especially in terms of data collection and preprocessing. Finally, in Sections III.2.4 and III.2.5, the results of the method applications are discussed, and future research opportunities are pointed out.

III.2.2 Theoretical Background and Related Literature

Throughout this Section, the main topics of this paper will be presented, beginning with technology and its development, and concluded by examining work related to this paper. Thus, this Section lays the theoretical foundation for our analysis

III.2.2.1 Technology Life Cycle Development

Technology is defined by literature in two ways. The first approach follows the neoclassical economic conception of technology, which describes innovation similarly to a production function (Sahal, 1985). The second approach has been named ‘Pythagorean view’ (Sahal, 1981) or ‘Bibliometrics’ (Watts and Porter, 1997) and describes innovation in terms of patent statistics. Therefore, we can describe technology development as the change in the production function over time or as the change in the number of publications over time. Closely linked to these concepts of technology is the idea of innovation. Innovation is defined by Rogers as “[…] an idea which is perceived as new by an individual” (Rogers, 1962). Newly developed technology can therefore be described as an innovation for any person merely learning about it. The way innovation is perceived in society and how innovations spread throughout it has been explored by Rogers in his fundamental research on innovation and the diffusion of innovation (Rogers, 1983). Rogers investigates the different factors required for an innovation to find widespread adoption in society.

Beyond Rogers's work, the progress of innovations has been subject to the Product Life Cycle (Klepper, 1997), the Technology Life Cycle (Abernathy and Utterback, 1978), and the Industry Life Cycle (Agarwal and Sarkar, 2002). These approaches explore innovation either on a product, technological or industrial level with all of them sharing the idea of cyclic development of innovations. The theoretic frameworks of the Product Life Cycle, the Industry Life Cycle and the Technology Life Cycle are closely linked to each other. These models have been applied in the form of a Hype Cycle, creating an intuitive illustration of the theories by plotting the evolution of technologies in more general terms. With growing interest from researchers and practitioners, these models have become a staple in innovation research. The most prominent one among these models is the Gartner Hype Cycle, introduced in 1995 (Dedehayir and Steinert, 2016).

The Hype Cycle model is characterized by the development of the expectations projected on new technologies over time. The curve representing the expectations originates from the hype surrounding the emerging technology and its business and engineering maturity as displayed in Figure III.2-1.

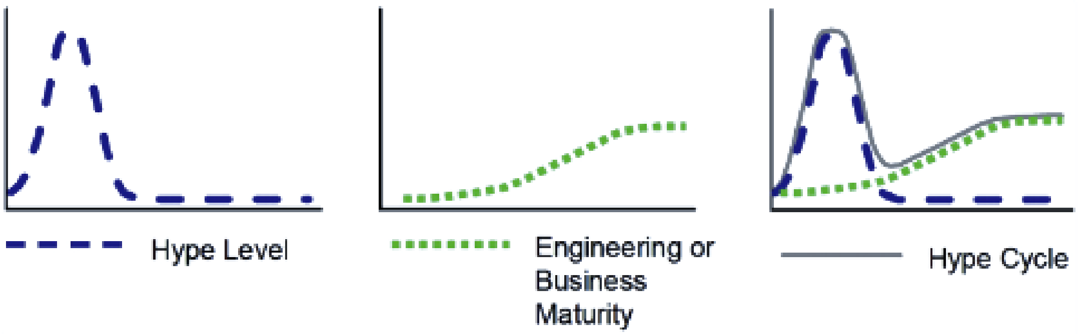

Figure III.2-1 The two curves forming the hype cycle (Dedehayir and Steinert, 2016)

Gartner’s resulting Hype Cycle (see Figure III.2-2) splits the development into five stages, namely the ‘Innovation Trigger’ the ‘Peak of Inflated Expectations’ the ‘Trough of Disillusionment’, the ‘Slope of Enlightenment’ and the ‘Plateau of Productivity’. Emerging technologies follow this path at different speeds and do not necessarily finish the entire development process to reach maturity (Steiner and Leifer, 2010).

This idea of cyclical development has prevailed in hype-cycle models that have become popular among practitioners, although the cyclical course has not yet been sufficiently empirically investigated (Jarvenpaa and Makinen 2008).

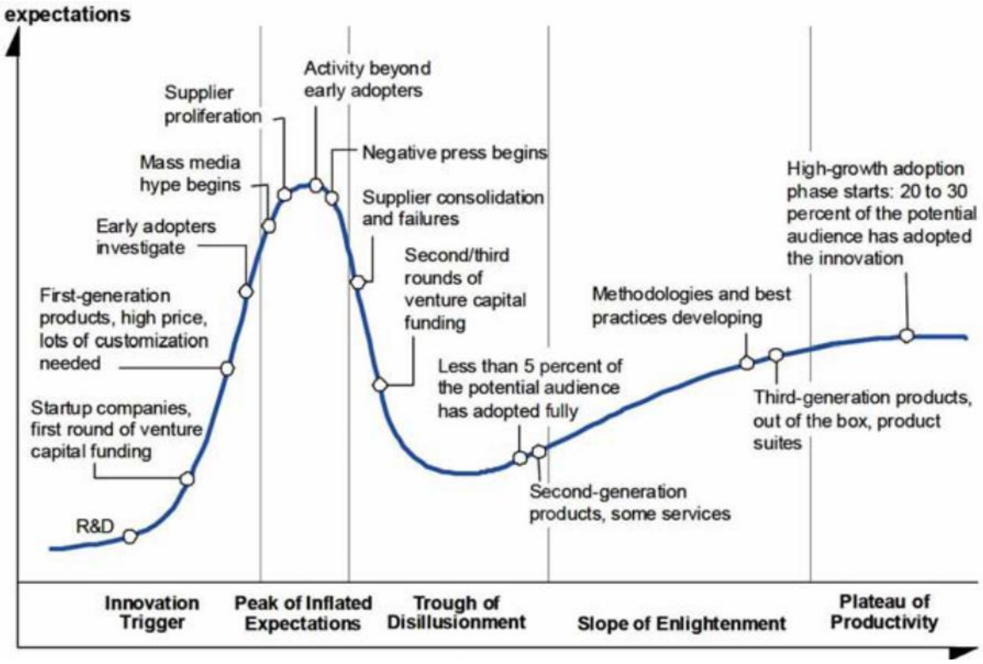

Figure III.2-2 Gartner’s Hype Cycle and its stages (Steinert and Leifer, 2010)

III.2.2.2 Related Work

Recent literature has made attempts at empirically proving the Hype Cycle and in coherence with it the underlying theories. These attempts often analyze the development of selected technologies to make their point. Throughout this Section, these works are outlined, deriving a resulting research gap from them, which will be the main point addressed by this paper.

One significant attempt at empirically detecting Hype Cycles has been made by Dahlberg and Hørluck, exploring whether the NASDAQ stock exchange development between 1998 and 2003 showed resemblance to the Hype Cycle (Dahlberg and Hørlück, 2001). This work uncovers parallels in the development but fails to prove sufficient causality between the stock quotation of technology companies and the public visibility of their technology, as the visibility is relevant for the Hype Cycle. Jarvenpaa and Makinen (2008) made another renowned attempt focusing on the evaluation of a technology's visibility using bibliometric measures. For this purpose, they searched the LexusNexus database for different technologies, plotted and evaluated the resulting charts with regards to their resemblance to the development proposed by the Hype Cycle model. Although they found general conformance, the visibility pattern differed between different data sources, mostly due to the professional press focusing on early adopters of the technologies, therefore showing an earlier interest than indicated in other, more ‚mainstream' sources. Despite that, both groups exhibited developments resembling the Hype Cycle.

Several researchers have done further work in empirically detecting the Hype Cycle. Thereby almost all studies have in common that they only focus on only a small number of investigated technologies (usually one technology), e.g., Hybrid Car (Jun, 2011) or Biofuels, Hydrogen and Natural gas (Alkemade and Suurs, 2012), but not using a more comprehensive range of technologies and their development. Further, primarily research focusses on simple statistical approaches like time series by article counting in all English language news or mainstream newspaper (e.g., van Lente et al., 2013). Only Rachul and Zarzezcny (2012) uses scientific journals as a source to investigate the development of neuro-imagining technology. On the other hand, studies focusing on information analysis of mass data regarding technology devolvement (e.g., Kim et al., 2012; Kim et al., 2011; Dereli and Durmusoglu, 2009; Kim et al., 2008; Rann, 1998; John, 1995; Campbell, 1983) concentrate mainly on information analysis and new opportunity discovery to derive future forecasting (decision support) systems.

However, all the empirical research previously mentioned fails to explore the differences in the diffusion of new technologies across different driving audiences – industrial and scientific research. Even though Järvenpää and Makinen (2008) observe the differences between target audiences in their work, they do not further explore correlations between the target audiences and possible causalities.

Therefore, the main contribution of this paper will be the exploration of the interest of different driving actors in the development of new technologies at different points in time. Based on that, our objective is to identify the developmental path of technologies with regard to the typical hype cycle course. For this purpose, research activities by practitioners in the industry are compared to research work carried out by research institutes, among others, by applying ARMA(X) models to the collected data basis. The imposing question in this setting is the quest for possible correlations and causalities between the different actors as formulated in the research question before. The interests of both scientific and industrial researchers will be measured by developing an empirical methodology to answer this question.

III.2.3 Methodology

The methodology used throughout this paper is based on the diffusion of innovation by Rogers, first introduced in 1962 and adopted by researchers ever since. Rogers describes the process as an innovation being “[…] communicated through certain channels over time among the members of a social system.” (Rogers, 1962). Using this concept, Rogers links the process of spreading innovation throughout a social system to the underlying innovative ideas being actively communicated. Therefore, his concept implies that the diffusion of innovation in a social system can be observed by observing all messages containing these new ideas. All messages are transmitted through various channels, addressing different target groups. Communication with the broad population of potential adopters in a social system mainly happens through mass media channels. The communication to early adopters and the actual developers of the innovation happens through more specific channels (Rogers, 1983).

Building upon Rogers‘ work, Grupp (1992) developed a cognitive model of innovation wherein the diffusion of innovation is just one of “six types of innovation-related functions”. Grupp models a gradient between the theoretical development of an innovation and its application. Each of the six functions thereby receives a specific input and generates a specific output.

The output of the first function “Theory & model development” consists of scientific papers. The six functions can be interpreted as the path from the theoretical development of technical innovations to finalized end-user products. The first function is followed by the “Technical realization” of an innovation, which is followed up by the “Industrial development”. While the second function does not generate output, the third function outputs patent applications.

Rogers‘ diffusion of innovation implies that the diffusion of innovation happens through messages between different players in a social system, which does not conflict with Grupp's model. This theory was also adopted by Baskerville and Myers (2009) to measure the discourse on technology fashions. Going forward, we can build on Rogers‘ concept by analyzing the means of communication used between the players involved in the development of a technology, defined by Grupp as scientific papers and patent applications. By measuring the output of researchers working on specific technological innovations, we can observe their interest in these innovative technologies. According to Grupp’s model, scientific papers can furthermore be related to the development of theories and models of innovations, a field mainly covered by publicly funded researchers. Additionally, patent applications can be mapped out according to the industrial development of innovations.

This mapping process is not entirely accurate as publicly funded research groups can also register patents just like industrial researchers can publish scientific papers. However, as these cases represent a relatively small percentage of the total publications in both groups, this paper will neglect them and assume that scientific papers represent the main research interests of publicly funded researchers, while patent applications represent the interests of industrial researchers.

The search results include publications whose main subject is not the innovative technology being assessed, but its application in another field. As the goal of our methodology is the measurement of researchers‘ interest in specific technologies, these publications are still taken into consideration. They showcase the spread of a technology across other fields and give insight into the entirety of researchers‘ interest in this technology. The collected publications are therefore not additionally manually filtered according to their main topic.

III.2.3.1 Data Collection

For the data collection method, we built upon the methods of state-of-the-art research which strives to accumulate the current research state in a specific field or on a specific topic. For this purpose, a systematic literature analysis is commonly used (Fettke, 2006). This systematic literature analysis is broken down into five steps (1) Formulation of the problem, (2) Literature search, (3) Literature evaluation, (4) Analysis and interpretation (5) Presentation (Cooper and Hedges, 1994).

The first step, formulating the problem has already been completed in the first two Sections, mainly the literature review, of this paper. The second step aims to identify literature on the topic of interest and will be executed as a systematic search in online data bases. The third step focuses on filtering the compiled literature for impactful publications in the research area. The methodology of this paper skips this step, as all publications found, mentioning the technology by name, are a proof of the respective researcher's interest in the technology (Baskerville and Myers, 2009). Therefore, they are relevant in answering the research questions of this paper. However, the fourth and fifth steps mentioned above are not relevant for the data collection process of this paper because they dive too deeply into the relevant publications collected, which is not required of our research methodology.

To ensure a sufficiently large and meaningful data basis for the subsequent analysis, we perform data analysis for 15 technologies, each of which was included in the Gartner Hype Cycle for at least five years since 2008. A further requirement regarding our analysis is that the technologies have at least completed a large part of their hype cycle, i.e. at least the first three of the five hype cycle development stages. An expansion of the number of technologies would be possible easily due to the automated data collection but would not improve the quality of the analysis or possibly even distort it by technologies that were not sensibly selected (e.g. if they were only included for a short period in the hype cycle).

The 15 examined technologies are: 3D Printing, Augmented Reality, Autonomous Vehicles, Big Data, Bluetooth, Blu-Ray, Cloud-Computing, HDDVD, IoT, Natural Language Processing, RFID, Speech Recognition, Tablet PC, VirtualReality, VOIP.

As the test sample consists of concrete products (e.g. HDDVD) and loosely defined sets of technologies (IoT) or concepts (Augmented Reality) we ensure a comparison of academic and industrial research on different levels related to the technologies.

For the collection of paper publications, the databases of the Institute of Electrical and Electronics Engineering (IEEE) Xplore and the Emerald Insight were used. The IEEE Xplore database is a digital library published by the Institute of Electrical and Electronics Engineering (IEEE). It includes more than four million documents, covering the fields of electrical engineering, computer science and electronics (Institute of Electrical and Electronics Engineering, 2018). The Emerald Insight online database is a collection of more than 75,000 articles about management and technology, maintained by the Emerald Group Limited (Emerald Publishing, 2018). By utilizing our developed web scraper, we automatically accessed the IEEE Xplore and Emerald Insight websites by extracting the web pages content directly from its underlying HTML code (Sunil and Neelima, 2011). Analogous for the collection of patent publications, the Espacenet patent search offered by the European Patent

Office (EPO) was used. Espacenet operates a database including 100 million patents worldwide dating all the way from 1836 to the present day (European Patent Office, 2017).

To ensure a systematic data collection, we define a search string for each technology. These are then tested in a manual validation and iteratively adapted to ensure considering most part of related records. The final search strings presented in Table III.2-1 were employed to search the databases. The data collection process is similarly applied to both patent and paper publications. The information extracted from the databases includes the title, an abstract and the publication date of each publication. All data were collected on December 26th 2018 and saved offline for further processing.

III.2.3.2 Data Preprocessing

Following the process of preparing the data for analysis, consisting of the filtering of the collected data, the elimination of duplicates and the conversion of the datasets into the necessary format for the subsequent data analysis is described. All steps of the data preparation are automated and executed using Python scripts. The term ‘dataset’ will be used to describe a publication with all its features like title, abstract and publication date.

Due to the employment of multiple data sources for the collection of paper publications, duplicates in the collected datasets cannot be neglected. This is addressed by searching for duplicate Digital Object Identifiers (DOIS) and eliminating duplicates from the entirety of collected datasets. DOIs were introduced in 2000 by the International DOI Foundation and offer unique identifiers for digital documents (Paskin, 2002). Although most publications dating from before the introduction of DOIs have received ex-post DOIs, it cannot be assumed that all paper publications have a DOI. Therefore, all datasets without a DOI are compared by title and displayed for a manual check. All duplicates are then excluded in this manual check and the unique datasets are added to the rest of the automatically filtered datasets.

Subsequently, we filtered the remaining datasets once again according to the defined search strings. This step ensures the ruling out of possible errors in the data sources search engines and differences in the search algorithms of the IEEE Xplore, Emerald, and EPO databases. Automated with the help of a Python script, all characters are converted to lower case characters. Using practical regular expressions (regex) the datasets are then filtered. Regular expressions are a standard textual syntax to represent patterns used for matching strings of characters (Paskin, 2002). For example, the regular expression “augmented(.?|\s)reality” will match for any patterns in a string, consisting of the string “augmented” followed by zero or one or characters of any type, including whitespace characters and then followed by the string “reality”. Therefore, it will match for the string “augmented reality” as well as “augmented-reality”. Regular expressions ensure that the filtering process is conscious of the different notations of specific technologies.

Based on the keywords of the search strings in the online databases, we define a regex for all technologies, according to the standard definition of regexes (Paskin, 2002).

The regexes shown in Table III.2-1 are used as the input for the “findall()” function of the “regex” library. Automating the filtering process using the “findall()” function of the Python “regex” library, the number of matches between title and abstract of a dataset and the employed regex is returned. All matches in the abstract and the title are then added to the respective dataset as new features. Afterward, fore each technology, all datasets are reduced to the features “Number of mentions in title”, “Number of mentions in abstract”, “Year” and “Is patent” and stored in a .csv. The “Is patent” flag is used to distinguish between papers and patent publications. Table III.2-1 shows the search strings and their corresponding regular expressions as well as the number of collected and prepared datasets.

Technology	Search string	Regex	Data-source	Datasets collected	Datasets after preparation
3D Printing	"3D Printing" OR "Inkjet Manufacturing"	"3D.{0,2}printing", "inkjet.{0,2}manufacturing"	EPO	8,711	8,623
			Emerald	626	522
			IEEE	1,373	1,174
Augmented Reality	"Augmented Reality"	"augmented(.?|\s)reality"	EPO	9,890	8,234
			Emerald	10.552	8,385
			IEEE	8,127	6,936
Autonomous vehicles	"Autonomous Vehicles"	"autonomous.{0,2}vehicles"	EPO	1,852	1,724
			Emerald	101	89
			IEEE	2,303	2,276
Big Data	"Big Data"	"big.{0,2}data"	EPO	8,158	6,883
			Emerald	1,647	1,565
			IEEE	20,759	18,438
Bluetooth	"Bluetooth"	"bluetooth"	EPO	42,257	40,371
			Emerald	652	593
			IEEE	9,537	9,318
Blu-Ray	"Blu-Ray"	"bl.{1,3}ray"	EPO	745	693
			Emerald	4,202	4,102
			IEEE	215	184
Cloud Computing	"CloudComputing"	"cloud(.?|\s)computing"	EPO	6818	6124
			Emerald	6135	5909
			IEEE	3934	3878
HDDVD	"HDDVD"	"hd.{0,1}dvd", "dvd"	EPO	826	725
			Emerald	603	547
			IEEE	61,686	8,493
IOT	"IOT" OR "Internet of Things"	"IOT", "internet.{0,2}of.{0,2}things"	EPO	9,863	9,351
			Emerald	9,531	8,562
			IEEE	36,981	34,712
Natural Language Processing	"Natural Language Processing" OR "NLP"	"natural.{0,2}language.{0,2}processing", "nlp"	EPO	1,969	1,799
			Emerald	1,207	1,064
			IEEE	15,952	13,596
RFID	"RFID" OR "Radio Frequency Identification"	"rfid", "radio.frequency.identification"	EPO	45,150	39,224
			Emerald	1,646	1,603
			IEEE	17,144	13,252
Speech Recognition	"Speech Recognition"	"speech.{0,2}recognition"	EPO	12,590	11,448
			Emerald	464	426
			IEEE	24,737	23,414
Tablet PC	"Tablet PC" OR "Tablet"	"tablet.{0,2}pc", "tablet"	EPO	1,817	1,621
			Emerald	3,712	3,377
			IEEE	511	463
Virtual Reality	"Virtual Reality"	"virtual.{0,2}reality"	EPO	9,737	6,723
			Emerald	17,425	13,541
			IEEE	23,339	18,462
VOIP	"VOIP"	"voice.{0,2}over.{0,2}ip", "voip"	EPO	6,457	5,855
			Emerald	3,104	2,978
			IEEE	4,428	4,013

Table III.2-1 Search Strings, corresponding regexes, number of collected and prepared datasets

III.2.4 Analysis

The preprocessed data demonstrates the typical characteristics of a time series, displaying sequential observations neatly organized in a specific timeframe (Campeanu and Salomaa, 2003). Therefore, we use established tools of time series analysis to conduct an in-depth analysis of the collected publications. In the first step, the data is adequately plotted and inspected. Secondly, an autoregressive-moving-average model (ARMA model) is fitted to the data, using relative datasets. Thirdly, an ARMAX model is adapted for the data, introducing the paper publication time series to the prediction of the patent publication time series. The ARMA- and ARMAX models are commonly used in economic sciences, engineering and social sciences to analyze time series graphs and predict future. The results of adopting these models are then compared and analyzed to answer the main research question of this paper.

III.2.4.1 Time Series Analysis

As a first example, the number of paper and patent publications concerning ‘Augmented Reality’ in the years 1995 to 2017, are plotted in Figure III.2-3. The data is displayed as the relative number of publications in any given year on the y-axis and the time in years on the x-axis.

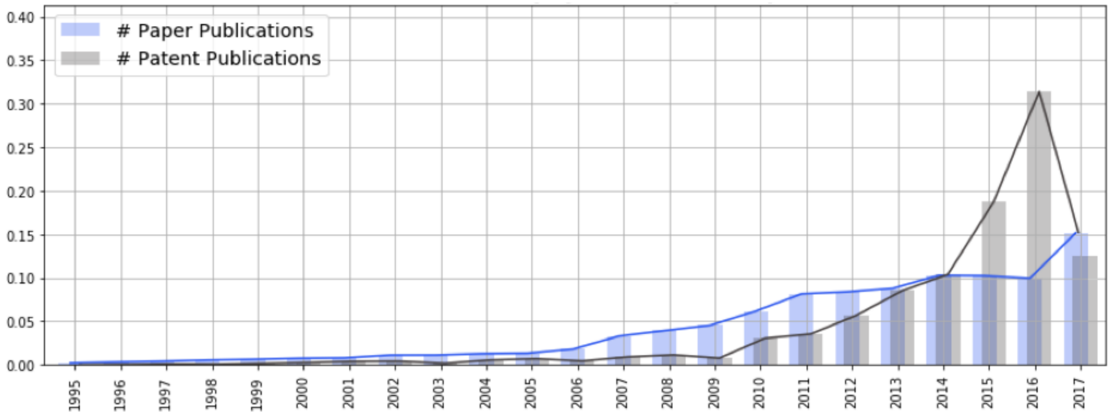

Figure III.2-3 Relative number of paper and patent publications on ‘Augmented Reality’

The relative number of publications is calculated by dividing the number of publications per year dealing with the technology by the sum of all publications ever published on that technology. By taking this additional step, the total number of paper publications compared to the total number of patent publications is irrelevant. The resulting curves display the development of the interest of both scientific and industrial researchers and exhibit a clear resemblance to the Hype Cycle patterns. After a steep rise in the number of publications, the number proceeds to abruptly drop. The recovery of researchers’ interest cannot yet be observed in the graphs displayed above, indicating a development called ‘Hype-disappointment’ (Cryer and Chan, 2008).

In the time series above, the first significant rise in publications can be observed with paper publications, starting around 2006. Patent publications follow this trend with a delay of roughly four years.

Similar time lag patterns can be observed for the other investigated technologies. In addition to paper publications reaching significant numbers at an earlier time, the relative increase in publications per year is lower as compared to the patent curve. In contrast, the patent curve spikes later but sharper, to the point where 30% of the overall issued patents on a certain technology are issued within the frame of one year.

III.2.4.2 ARMA(X) Analysis

To further investigate these findings, an ARMA and an ARMAX model will be used. Both have obtained a great interest in modeling real-world processes (Campeanu and Salomaa, 2003). We adapt an ARMA and ARMAX model to the data to improve the understanding of the findings and potentially predict future values in the series. Thereby, we base our analysis on the Box-Jenkins approach, which has been widely used in the literature because of its performance and simplicity.

Since the curve resulting from the number of publications per year ideally represents the process of a technology passing through the Hype Cycle model just once, a time series capable of being adapted into an ARMA(X) model must be created by combining the time series models for all reviewed technologies into a single joint time series. For the creation of this joint time series, the relative number of publications per year is utilized. The very first publication for each respective technology can be observed many years before the relevant, significant rise in the number of publications. This issue is resolved by looking at the percentage of total publications per year and starting the observation period when this percentage surpasses 10 percent.

For the construction of the final joint time series all 15 collected technologies data have been included. To negate the effect of the chronological order in which the single time series have been merged, the order is randomized and a random set of 10 of the resulting joint time series is selected for the ARMA models. It should be highlighted that all generated time series are based on the same data, the only difference lies in the order of the combined technologies. Figure III.2-4 shows the plot of two of the 10 resulting time series.

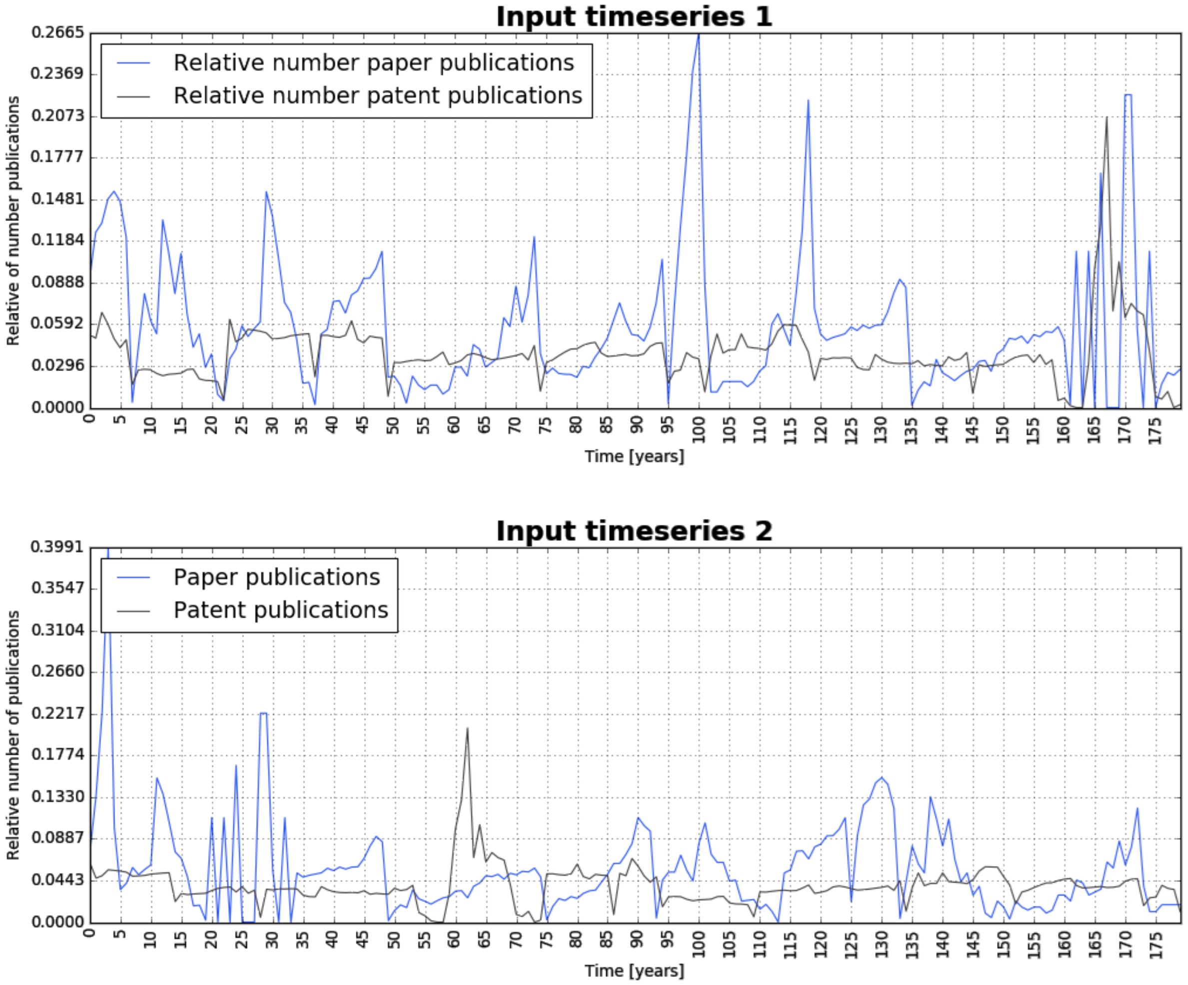

Figure III.2-4 Resulting time series for paper and patent publications

ARMA Model. A general time series x_t can be modeled as a combination of past x_t values and/or past e_t errors.

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$$

The four steps of the Box-Jenkins approach required to model real-life time series based on the equation are defined as follows:

“First the original series, x_t must be transformed to become stationary around its mean and its variance. Second, the appropriate order of p and q must be specified. Third, the value of parameters $\phi_1, \phi_2, \ldots, \phi_p$ and/or $\theta_1, \theta_2, \ldots, \theta_q$ must be estimated using some non-linear optimization procedure that minimizes the sum of square errors or some other appropriate loss function. Finally, practical ways of modelling seasonal series must be envisioned and the appropriate order of such models specified.” (Makridakis and Hibon, 1997).

For the usage of *equation (1)*, the time series must be stationary around its average (mean) and its variance. The Box-Jenkins methodology suggests the use of differencing or transformations to achieve stationarity. As neither of these methods improves the prediction accuracy for short prediction horizons (Makridakis and Hibon, 1997), these methods are not applied to the data in this paper. A constant average over time is estimated using the earlier established relative number of publications per year. As a result of this approach, the sum of the relative numbers of all publications for each individual technology equals 1.

Based on an examination of the autocorrelations and partial autocorrelations of the stationary series, the order of the ARMA model is found. Guided by *Box and Jenkins* practical rules, the values p and q are determined. Any model which results in random residuals can be deemed appropriate according to the Box-Jenkins methodology (Dedehayir and Steinert, 2016).

The non-linear optimization procedure, based on the steepest-descent-method, is applied to estimate the parameters of p and q as well as their respective counterparts P and Q. The resulting estimation has no significant deficits except for the inability to guarantee a global optima (Makridakis and Hibon, 1997). Diagnostic checks are executed by examining the residuals of the actual values minus those estimated through the model to be random. After meeting this requirement, the model is deemed appropriate (Makridakis and Hibon, 1997). Carrying out these steps, the optimal parameters for the ARMA model are $p = 1$ and $q = 5$.

Following the parameter determination, the ARMA model is tailored to the paper and patent time series and the model's prediction quality is evaluated. This process is done for each of the 10 joint paper and patent time series. Representatively used in this Section is the time series shown in Figure III.2-4.

In order to appropriately adapt the ARMA model for the task at hand, we used two-thirds of the time series to tailor the model to the available data and the remaining one-third of the time series to check the predictions made by the trained model. With each of the time series having a length of 180 data points, 120 are used for model adaption and the remaining 60 are used for testing. For each of the predicted 60 test-data points, the predicted value is compared to the actual value.

The average squared error of all the predictions is then calculated. Exemplarily for one of the joint time series, Figure III.2-5 plots the predictions made by the ARMA model and the actual values of the time series.

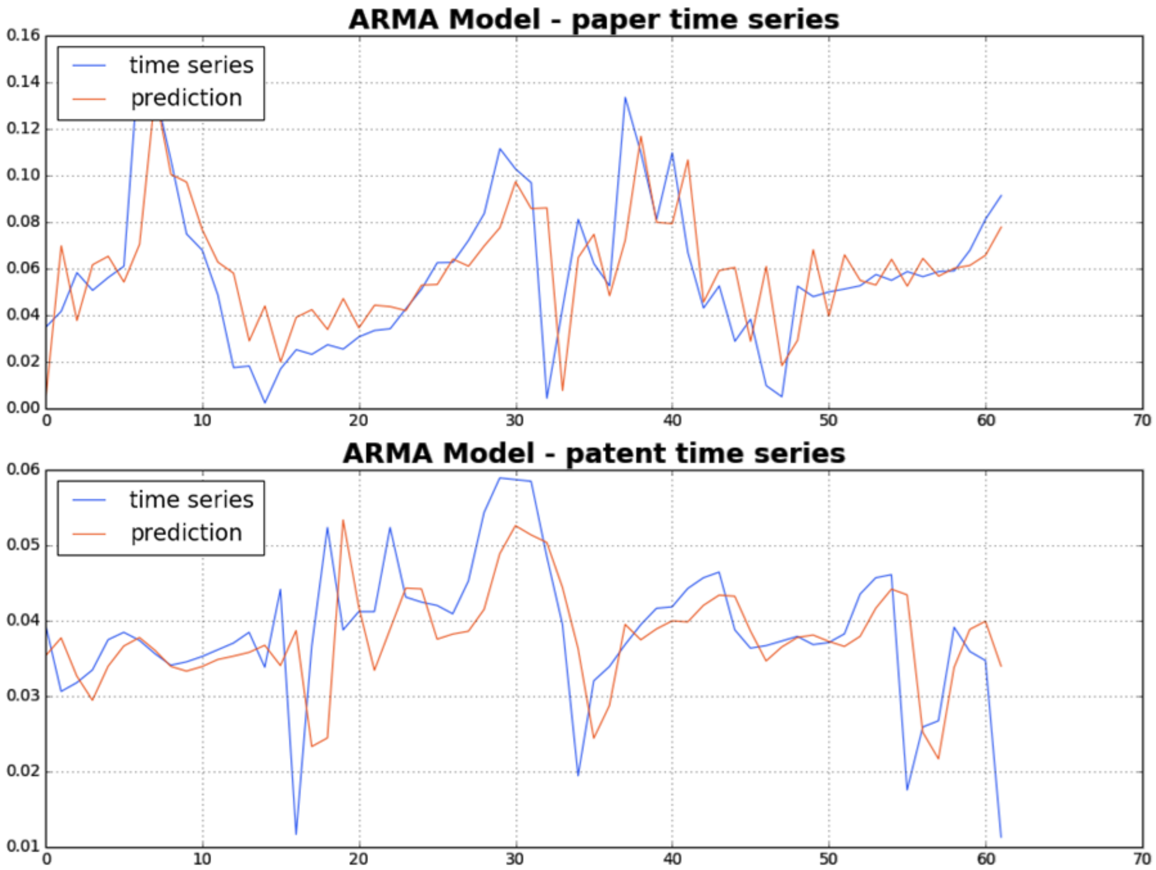

Figure III.2-5 ARMA Model predictions for paper and patent time series

The model for the exemplarily joint time series shown in Figure III.2-5 results in an average squared error of *0.0029902023437655295* for the paper time series and an average squared error of *7.458191611099676e-05* for the patent time series. The predictions of all 10 models have a mean squared error smaller or equal to *0.0038* for the models trained on the paper time series and a mean squared error smaller or equal to *0.00093* for the models trained on the patent time series.

ARMAX Model. An approach, consistent with previous literature (Makridakis and Hibon, 1997), to possibly improve prediction of the ARMA accuracy is to introduce an explanatory variable (X). As observed in Figure III.2-3, the paper time series exhibits a development very similar to one of the patent time series but with a time lag. Therefore, we assume that the patent time series prediction will profit from the introduction of the paper time series to the model as an explanatory variable. The ARMAX model will be adapted and tested similarly to the process previously used for the ARMA model.

Consistent with the approach previously used for tailoring and testing, two-thirds of the time series are used for adapting and one-third is used for testing. The model parameterisation also remains the same, with p = 1 and q = 5. The predictions made by the finished model are compared to the actual values of the time series, calculating the average squared error. Figure III.2-6 displays the results of the model adapted to the previously used joint time series.

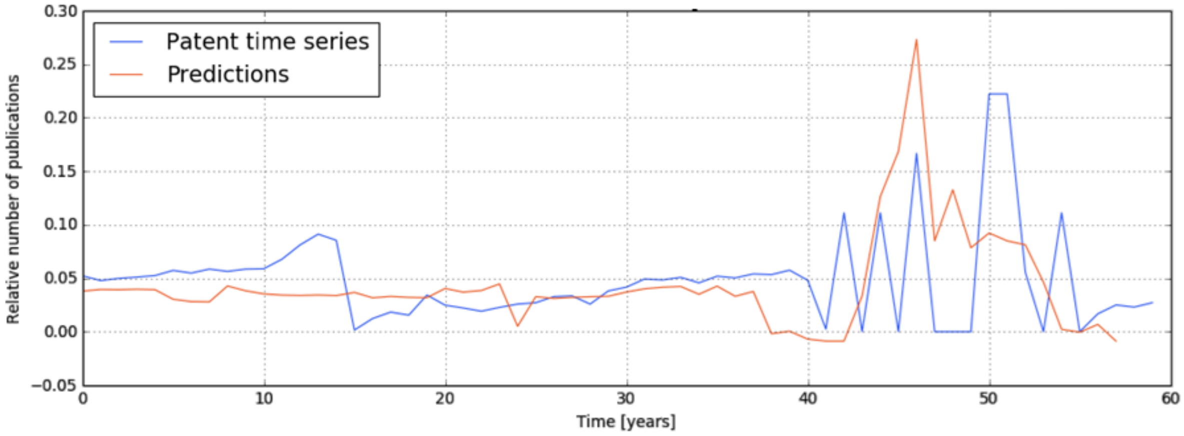

Figure III.2-6 ARMAX Model predictions and actual time series

Indicated by the plot in Figure III.2-6 and the resulting mean squared error of 0.004860898044744082 3, the model’s prediction accuracy has decreased after introducing an exogenous variable. A similar pattern manifests across the other nine time series to which the ARMAX model has been tailored.

III.2.4.3 Analysis Conclusion

As previously stated, the first significant spike of publications can be observed in the number of paper publications and afterward, with a certain time lag, in the number of patent publications. This pattern is consistent for all 15 technologies inspected in this paper. Based on this observation, we can derive the statement that academic researchers appear to be leading in adopting emerging technologies and innovations, later followed by their counterparts in practice-oriented research, which show a more substantial peak of interest. This behavior may be primarily caused as academic researchers conducting more fundamental research on new technologies, which naturally happens before the more applied research is carried out by researchers in the industry. However, an investigation of the reasons for this behavior is part of further research as the main objective of this paper is to examine the development path quantitatively. Beyond that, the paper and patent data arguably showed developments consistent with hype curves. However, the ideal hype curve as outlined by Gartner's Hype Cycle could not be achieved. Instead, the time series plots regularly show multiple peaks, which corresponds to the hype developments found by prior research (Cryer and Chan, 2008).

Next to the time series analysis, the ARMA model has proven its prediction qualities for paper and patent publication curves, exhibiting low mean squared errors. As the time series used for the ARMA model are obtained by appending the individual technology curves to a joint time series, the development curves of previous technologies can be used to predict the development of another technology. Accurate prediction results indicate similarities in the development of different emerging technologies. Nevertheless, the usage of paper publications to improve the prediction capabilities of the patent publications in the ARMAX model has proven to decrease the prediction accuracy. Consequentially, there appear to be differences in the underlying dynamics of paper and patent publications.

Compiling the results of the time series analysis and the ARMA(X) models, the research question can be answered twofold. A clear lead of academic researchers in publicizing new technologies is observed, with industrial researchers following in suit later on as indicated by the results of the time series analysis. The development paths of technologies could be used to predict the development paths of emerging technologies. However, the correlation between the number of publications from academic researchers and those from industrial researchers remains unpredictable using just the methods employed in this paper, as the usage of paper publications for the prediction of patent publications did not improve the results.

III.2.5 Implications, Limitations and Outlook

The development of technological innovations is a complex process with a wide range of stakeholders, involving the activities of industrial and scientific research. This paper was driven by its research questions whether the academic or the industrial researchers are leading in the development of new technologies and, based on that, how to identify the developmental path of technologies with regard to the typical hype cycle course.

In a first step towards answering this question, existing research was reviewed. Next, patent and paper data were automated collected for 15 chosen technologies and analyzed by time series and ARMA(X) models to derive possible correlations and causalities between R&D activities by practitioners in the industry and research work carried out by research institutes.

From an empirical point of view, the results of this study imply a complex relationship between the work of academic researchers and their counterparts in practice-oriented research. The results enable companies to improve their assessment of the technology development, e.g. when deciding on an appropriate investment. Furthermore, the paper provides a basis for further research, which may be directly used in decision support, e.g. to anticipate the success probabilities of specific technologies. However, the limitations of the methodology must be taken into consideration. The data used in this paper is limited in its sources, the number of datasets and the diversity of data types included. Therefore, the methodology may profit from more data sources and the introduction of new data types, like online search engine traffic or newspaper articles. An expansion and clustering of the examined technologies into different fields and the analysis of dynamics between and across these fields may promise to yield formidable results.

The ARMA(X) models used in our approach are already considerably more complex than most approaches from previous studies, but a possible next step would be to apply more sophisticated machine learning approaches to the collected data as the amount of available data indicate a promising approach. It would also be conceivable to use such approaches to derive predictions about the future development and success probabilities of technologies.

Another interesting approach for further research is the role of academic and industrial researchers on the level of completed and institutionalized technologies. Understanding their role and interaction on this level might help with understanding their impact on each other and the underlying technology. Complementing this, research on the influence of other parties in innovation systems like governments and universities on these researchers is of great interest.

Despite the approaches' limitations that offer possibilities for future research, our results contribute to the investigation of the role of academic and industrial researches in the empirical research of emerging technologies.

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III.3 Research Paper 4: “Determining Optimal Strategies for Investments in an Emerging IT Innovation”

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Abstract: *To generate competitive advantages through investments in emerging IT innovations, an economically well-founded investment strategy is of decisive importance, since timing and extent of investment amounts considerably determine the associated risk and return profile. Due to the uncertainty about emerging IT innovations, an early market entry time is associated with high risk, but offer high returns. A later market entry may carry lower risk but only offers lower returns. To take advantage of both investment strategies while reducing their disadvantages, a mix of both investment strategies can be advantageous. Companies often choose strict early or later investment strategies since an adequate assessment of possible combinations, opportunities and risks is not carried out in advance and company- and innovation-specific factors are neglected. Thus, we develop a quantitative optimization model enabling the determination of an optimal investment strategy and budget allocation to the two different investment strategies in the sense of maximizing the investment´s overall NPV supplementing previous studies by considering company- and IT innovation-specific factors. We show that strict investment strategies are often disadvantageous, that the amount of the investment budget influences the innovation´s*

expected NPV and that the company's innovativeness has a strong influence on the innovation budget allocation.

III.3.1 Introduction

The role of information technology (IT) in the field of innovation has often been discussed (Melville et al., 2004) and studied for decades (Johannessen, 1994; Bengtsson and Ågerfalk, 2011). As we are in an era of new technological advances and high competition, the question of how a company can keep pace with competition through organizational innovation and maintain sustainable long-term success (Sedera et al., 2016) is still of central interest. Given trends such as smart manufacturing, internet of things (IoT), mobile computing, social media and the proliferating digitalization, most emerging innovations are inseparably intertwined with information technology. For a majority of companies, investments in emerging IT innovations have become an indispensable challenge since such investments require substantial financial funds and at the same time, pose considerable risks (Lu and Ramamurthy, 2010; Swanson and Ramiller, 2004). However, such investments require substantial financial funds and at the same time, pose considerable risks given that many emerging IT innovations are likely to be failing because of missing customer acceptance due to missing fulfillment of customer expectations and needs (Lu and Ramamurthy, 2010; Swanson and Ramiller, 2004). Thus, investments in emerging IT innovations have to be mindfully managed through economically well-founded evaluation approaches, as ignoring such investments can limit the inherent benefits of applications that the underlying technologies can offer (Nwankpa et al., 2013).

Therefore, in a first step it is helpful to consider the concept of “hype cycles” by Gartner Inc. (e.g., Panetta, 2017), according to which the uncertain development of an emerging IT innovation is characterized by different stages of maturity. At the beginning of an “*emerging*” innovation´s development the innovation is often accompanied by rumors and hypes (Abrahamson, 2009) and investments are associated with high risks (Zhou et al., 2005; Wind and Mahajan, 1997). Over time, the IT innovation becomes more and more sophisticated turning into a “*mature*” innovation. In this way, the innovation gains more and more acceptance by customers which leads to a broader diffusion and adoption making investments less risky (Dos Santos, Brian L and Peffers, 1995). As soon as the innovation has been widely accepted by customers, it has been established, i.e., “institutionalized”. However, the Gartner Hype Cycle does not provide any economic guidance with regard to the question of when to invest into a certain IT innovation. In particular, it provides neither information on opportunities and risks nor information on the economic potential of IT innovations. To be able to make economically well-founded investment decisions, adequate valuation approaches have to be developed that carefully consider the chances and risks of IT innovations with different maturity. This is of essential importance, as the chance and risk profile of such investments considerably changes over the life cycle of the respective IT innovation.

Because of their novelty and immaturity, emerging IT innovations offer companies that invest as *first mover* (FM) the chance to achieve a high level of awareness among customers (Mittal and Swami, 2004). Because of their high level of awareness, FM can quickly generate high market shares (Robinson, 1988; Kerin et al., 1992) and build up much knowledge due to their early market entry. This can lead to a technological leadership and enables them to “impose significant knowledge barriers that early adopters have to overcome” (Schmalensee, 1980; Ravichandran and Liu, 2011), in order to compete successfully against established FM. In contrast, later investments as *late mover* (LM) in mature IT innovations are often associated with lower risks since the development and adoption status of the underlying technology are already visible (Meade and Islam, 2006; Dos Santos, Brian L and Peffers, 1995). Mistakes that FM made in the development of emerging IT innovations are well known by LM and can thus be avoided (Hippel, 1982). Furthermore, LM rely on already partially developed technologies and continues to develop it further, which induces lower costs than completely redeveloping an innovation (Dos Santos, Brian L and Peffers, 1995). Additionally, they benefit from an already existing pool of customers, whose expectations and needs are already known, thereby reducing the risk that the innovation will fail (Dos Santos, Brian L and Peffers, 1995).

Given the complex trade-off and owing to management uncertainty, e.g., due to the lack of relevant data, companies often tend to apply a strict black-or-white investment strategy (i.e., a pure FM or LM). However, a “mixed” investment strategy (i.e., one part of an investment budget is allocated to a FM investment and the other part to a LM investment) entails the possibility of combining the advantages of a FM and a LM strategy and avoiding their disadvantages at the same time to reach a superior risk and return profile and outperform strict FM or LM strategies. Therefore, an economically well-founded ex-ante evaluation, regarding an optimal allocation of the budget to emerging and mature innovations is needed at an early stage since FM advantages cannot be realized later on once an IT innovation emerges. Beside the chances and risks of the different investment strategies (emerging vs. mature) it is also important to identify relevant specifics of the underlying IT innovation (e.g., estimated market impact in different scenarios) and the company (e.g., company’s ability to innovate successfully) that can significantly influence the investment decision. This allows us to cover various essential framework conditions to derive fundamental hypotheses regarding scenarios in which investing as FM in an emerging innovation is beneficial towards investing as LM in a “mature” innovation.

To the best of our knowledge, there is no quantitative optimization model, combining relevant company- and innovation-specific parameters, success- and failing-probabilities and considering a “mixed” investment strategy to calculate the optimal allocation of an investment budget for emerging and mature IT innovations to maximize the NPV´s of the underlying investments. Conducting sensitivity and scenario analyses, we aim to uncover relations between the identified parameters thus enabling a deeper understanding of how different parameters influence the optimal allocation of an investment budget. Thereby, we contribute to one of the fundamental research questions in IT innovation literature of *when* and *to what extent* a company should invest in an emerging IT innovation with deriving the following two research questions (RQ´s):

RQ1: *How can a company determine the optimal strategy for investments in an emerging IT innovation regarding the expected NPV?*

RQ2: *How do different company- and IT innovation-specific factors influence the optimal strategy and the expected NPV of investments in an emerging IT innovation?*

The remainder of this paper is organized as follows. Following a discussion of the relevant literature in Section III.3.2, Section III.3.3 develops our quantitative optimization model. Section III.3.4 presents the model’s solutions, exemplary applications, and sensitivity analyses. Section III.3.5 summarizes the findings and limitations and provides suggestions for future research.

III.3.2 Theoretical Background and Related Literature

In this Section, we draw on IT innovation literature to define IT innovation and its possible development inspired by the concept of hype cycles. We also discuss the literature on investments in emerging IT innovations and parameters influencing decisions regarding optimal investment strategies. Thus, this Section lays the theoretical foundation for our quantitative optimization model.

III.3.2.1 IT Innovations

Swanson (1994) defines IT innovations as “innovations in the organizational application of digital computer and communications technologies (now commonly known as information technology).” Garcia and Calantone (2002) define (IT-)innovation as the generation and/or acceptance of ideas, processes, products, and services that are new to the company or the company´s customers. It is a generalized view of innovation taking into account innovation occurring in all kind of organizations. It goes beyond the definitions that stated innovation as “new to the world” (Garcia and Calantone, 2002). We refer to a definition of Crossan and Apaydin (2010) that stated innovation as the “production or adoption, assimilation, and exploitation of a value-added novelty in economic […] spheres; renewal and enlargement of products, services, […]; development of new methods of production; and establishment of new management systems”. This definition includes internally initiated innovations, as well as adopted innovations.

Basically, we can distinguish two types of innovations. Depending on their “newness”, innovations can be incremental *(mature)* or breakthrough *(emerging).* Mature innovations refer to minor changes in technology or simple product improvements. In contrast, emerging innovations are novel, unique, or state-of-the-art technological advances in a product category (Wind and Mahajan, 1997; Zhou et al., 2005). Emerging innovations are highly risky to pursue (Zhou et al., 2005). On the one hand an emerging innovation may be technologically risky because developing state-of-the-art technology is extremely expensive and requires substantial investments (Wind and Mahajan, 1997). However, even if an innovation may be technologically straightforward, it can be extremely risky on the market side because the consumers acceptance is highly uncertain (Christensen and Bower, 1996).

An innovation’s development over time can be explained by Gartner Inc.’s concept of hype cycles (for the current version, see Panetta, 2017), which illustrates the possible developments of an emerging IT innovation through several stages. The development begins with a *technology trigger* with excess publicity, leading to over-enthusiasm and investments often influenced by bandwagon behavior. Thus, within their lifecycle of adoption (Rogers, 2003), IT innovations are often “hyped,” that is, accompanied by waves of discourse or rumors about the innovation itself and its adoption and diffusion (Abrahamson and Fairchild, 1999). This hype typically reaches a peak of *inflated expectations* before it fades away in a *trough of disillusionment*. For our upcoming model, we summarize these first three stages within a first of two development periods by mapping them through the first of two consecutive discrete points in time and refer to investments within these first three stages as FM-investments.

However, in this early stage, substantial adoption is missing, and evaluation with reliable estimations of future evolution is almost impossible owing to the hype that might fade in the absence of long-term productivity. Today, IT innovations such as Connected Homes, Blockchain and Machine Learning can be classified as *emerging IT innovations* (Panetta, 2017). In contrast, *mature IT innovations* have already been adopted by a substantial part of the market (Rogers, 2003), demonstrating that they were not just a hype and exhibiting stable development (Fenn and Raskino, 2008). Thus, their future evolution can be roughly estimated. For instance, virtual or augmented reality can be classified as mature IT innovations (Panetta, 2017). Only a few technologies will reach the status *"mature"* at the end of the first period of development and are worthy of further investment and hard work to understand the technology's applicability, risks, and benefits, leading to a *slope of enlightenment* followed by a *plateau of productivity* (Fenn and Raskino, 2008; Wang, 2010). For our upcoming model, we summarize these two stages within the second of two development periods by mapping two consecutive discrete points in time and refer to investments within these two stages as LM-investments. Finally, *institutionalized IT innovations* are innovations that have been established in the market and acquired mass adoption beyond the plateau of productivity. Also, they have crossed the chasm from being an IT innovation to an established technology. As the Gartner Hype Cycle only provides information about the current development status of an innovation and is not suitable for planning investments due to a lack of information about opportunities, risks and economic potential, we develop a mathematical model that calculates an optimal allocation of an investment budget to emerging and mature innovations on the basis of investment-related information specific to the innovation, market and company, which we will motivate and explain in more detail in the upcoming Section.

III.3.2.2 Investments in IT Innovations

The advent and massive proliferation of digitalization and its corresponding IT applications (e.g., mobile computing, cloud computing, social media, etc.), fueled by the consumerization of IT (Harris et al., 2012) provided companies with flexible and cost-effective opportunities to innovate (Vodanovich et al., 2010). Technology advancements over the past few years have assisted companies in innovation through a variety of helpful improvements and decision support systems (e.g. improved decision-making capabilities, increased customer connectedness, increased number of communication channels, enhanced communication facilities) (Huber, 1990; Brynjolfsson, 2011; Kumar et al., 2010; Bharadwaj, 2000; Nambisan, 2016). Therefore, investments in emerging IT innovations are beneficial to (Melville *et al.*, 2004) and essential for companies (Clark and Guy, 1998; Nadler and Tushman, 1999).

However, investments in new IT innovations remain a risky challenge, e.g. due to uncertainty about future market penetration and the literature does not provide any information on how an investment budget should be allocated optimally to IT innovations of different stages of maturity. Therefore investments are often driven by market pressure and bandwagon behavior (Häckel et al., 2017), thus lacking an economically well-founded decision calculus. In order to avoid investments on a gut feeling when choosing an optimal investment strategy, but considering the peculiarities of IT innovations (e.g., probability of institutionalization, expected economic impact of technology, or market innovativeness) and the current development status according to the Gartner Hype Cycle, our optimization model includes parameters that reflect these peculiarities and the current development status. To ensure that the investment decision is also optimal in an economic sense, we select the maximum net present value of the underlying investments as an optimality criterion. By applying such a model, complex interdependencies between key factors can be mapped and considered in investment decisions. Furthermore, we also consider company-specific factors (e.g., company size, investment budget, structure, and agility) influence the risk and return profile of investments in emerging IT innovations. Thus, a company's ability to understand, successfully adopt, and implement IT innovations are key factors as the introduction of new technologies imposes "substantial burden on the adopter regarding the knowledge needed to understand and use them effectively" (Ke and Wei, 2006). This ability to be a successful innovative company can be designated as a company's *"innovator profile"*. Companies that fit this profile are expected to innovate more easily, effectively, and economically (Fichman, 2004b). Furthermore, systematic innovators have more experience in selecting and implementing IT innovations in an early phase and can better evaluate new applications (Swanson and Ramiller, 2004). Thus, a company's success with investments in emerging IT innovations depends on not only on the underlying technology's customer acceptance but also the company's innovator profile (Fichman, 2004b). We incorporate the key capabilities mentioned by Ke and Wei (2006) and denoted as innovator profile in our model in the form of a further parameter. That makes it possible to consider effects caused by a high respectively low innovator profile mentioned by Fichman (2004b) on the optimal allocation of an investment budget.

When choosing a suitable investment strategy, the timing of the investment plays also a major role. Thus, depending on the investment timing, innovation investments undergo different risk and return profiles and some prior studies focused on the evaluation of emerging IT innovations and the effects on IT innovation investment strategies. For instance, Dos Santos and Pfeffers (1995) demonstrated advantages of engagements in emerging IT innovations given the possibility of adding over-proportional value. Lu and Ramamurthy (2010) examined investment strategies in stable and dynamic settings and demonstrated that proactive IT innovation leaders who regularly engage in emerging IT innovations outperform reactive IT innovators in overall performance and cost efficiency.

Wang (2010) found that companies improved their performance and gained a better reputation owing to over-proportional returns resulting from long-term competitive advantages based on investments in emerging IT innovations. Using game theory, Hoppe (2000) showed that under certain conditions, even second-mover strategies could be advantageous because of spillover effects. However, these studies neither incorporate the risk of non-institutionalization, nor provide advice about the extent and timing of investments, nor explain how an investment budget should be allocated between emerging and mature IT innovations. In a first approach, Häckel *et al*. (2013) considered the risk of a failing emerging IT innovation and examined the error resulting from fixed investment strategies regarding the allocation of periodical IT innovation investment budgets; however, they did not analyze the concrete decision situation of a company that aims to optimize the budget allocation over time for an emerging IT innovation.

However, there is a lack of quantitative approaches that investigate optimal “mixed” strategies e.g. in terms of timing and budget allocation that entail the possibility of a beneficial combination of a FM and LM investment to reach a superior risk and return profile and may outperform strict FM or LM strategies.

Furthermore, other insights into whether an investment strategy for an innovation will be successful are often based on statistical evaluations of historical data of similar companies with similar investment behavior (FM vs. LM). Therefore, by using those studies recommendations for a certain investment strategy can be given under known conditions. However, since these results cannot be generalized and transferred to other scenarios, investment strategy decisions cannot be made on economically well-founded basis in previously never occurred environmental scenarios.

In sum, the current status in relevant research primarily reveals gaps by either neglecting relevant (company-specific) parameters, focusing on strict investment strategies or building up on historical data which cannot be generalized and applied on different companies or scenarios.

Thus, drawing on related literature, the present study develops a quantitative optimization model to determine an optimal investment strategy considering relevant parameters in sense of calculating an optimal allocation of an investment budget to emerging and mature IT innovations. Using findings from prior research, we analyze the impact of different company- and IT innovation-specific influencing factors using exemplary applications and sensitivity analyses. This can provide new insights and propositions for future research and empirical testing.

III.3.3 Model

We consider a company that has decided to invest in an emerging IT innovation. Before making an investment decision, the company must determine the optimal strategy regarding timing and allocation of an available amount of "innovation budget" to maximize the innovation´s expected NPV. Our model covers strategies for a *„first mover"* investment in an emerging IT innovation, a *"late mover"* investment in a mature IT innovation, and the possibility of a mixed investment strategy, which might enable a superior combination of the LM and FM risk and return profiles. To cover the possibility of the IT innovation developing over time, the model's time frame comprises three points in time. A FM investment is possible at the first point in time wherein the IT innovation emerges, and a LM investment is possible at the second point in time. At the third point in time, the development of the IT innovation is complete, and its final destiny becomes obvious.

Assumption 1 – Initial Situation

At $t = 0$, a company chooses a strategic budget $B \in \mathbb{R}^+$ for an investment in an emerging IT innovation. At the same time, the company must determine the share $x \in [0; 1]$ of B invested at $t = 0$ (FM investment). The other share of budget $(1 - x)$ is saved for a possible investment at $t = 1$ (LM investment).

The provided budget serves as a basis for the planning of investments and should be immediately planned when a new IT innovation emerges to enable investments with the potential for FM advantages. If the budget is not completely exhausted in the FM investment, the remaining funds can be reserved for a possible LM investment in the same IT innovation. Therefore $x = 1$ represents a strict FM strategy, $x = 0$ is a strict LM strategy and $x \in (0; 1)$ a mixed strategy.

Assumption 2 – Uncertainty about IT Innovation's Development

a) Possible Scenarios for Development: *The development of an IT innovation is uncertain and broken down into two periods: from $t = 0$ to $t = 1$ (period one) and from $t = 1$ to $t = 2$ (period two). Within both periods, a positive (upside: "u") and negative (downside: "d")* *scenario is possible, whereas a positive scenario within period one implies a development into a mature IT Innovation and a positive scenario within the period two implies a development into an institutionalized IT Innovation. However, a negative development in both periods implies a failing IT Innovation. After a negative development within the first period, a second period of development is not considered because the IT innovation has failed. At* $t = 2$, *the IT innovation's development is completed and one of the scenarios* $s \in \{uu, ud, d\}$ *is realized.*

The breakdown of an IT innovation's development in two periods is inspired by Gartner's hype cycle (Fenn and Raskino, 2008) and enables an appropriate depiction of an IT innovation's development within our quantitative model. It covers the entire process from when an IT innovation emerges to the outcome (Wang, 2010). Thus, relevant changes in the characteristics of an IT innovation, which should be accounted for in an economically well-founded evaluation, can be adequately considered (e.g., decreasing uncertainty about the possible long-term success of an IT innovation).

b) Probabilities of the Development Periods: *The uncertainty about the future IT innovation development is described by the probability* $p_t \in [0; 1]$ *with* $t \in \{0; 1\}$ *for positive (u) development and* $(1 - p_t)$ *for negative (d) development within the first and second period. The probability for a positive development is considerably lower in the first than in the second period* $(p_0 < p_1)$.

The probability of positive development in the first period (p_0) indicates the probability of an emerging IT innovation is becoming a mature one. This probability is rather low since many emerging innovations fail after the first period of development when the hype vanishes (Gourville, 2006). When the IT innovation has survived the first period, it demonstrates marketability thus far and the first indications of market acceptance can be observed (e.g., sales of beta-versions or results of customer surveys). Meanwhile, other competitive IT innovations have already failed within the first period and thus, only those IT innovations that passed the first "endurance test" reach the second period of development and thus the risk of investing in a failing technology is getting lower. Therefore, the probability of a positive development in the second period (p_1) is considerably higher than the probability (p_0). The probabilities for the upside and first and second downside scenarios $s \in \{uu, ud, d\}$ can be calculated by the probabilities $p_t \in [0; 1]$ designated for the two periods of development (Figure III.3-1 Overview of the model's decision situationFigure III.3-1).

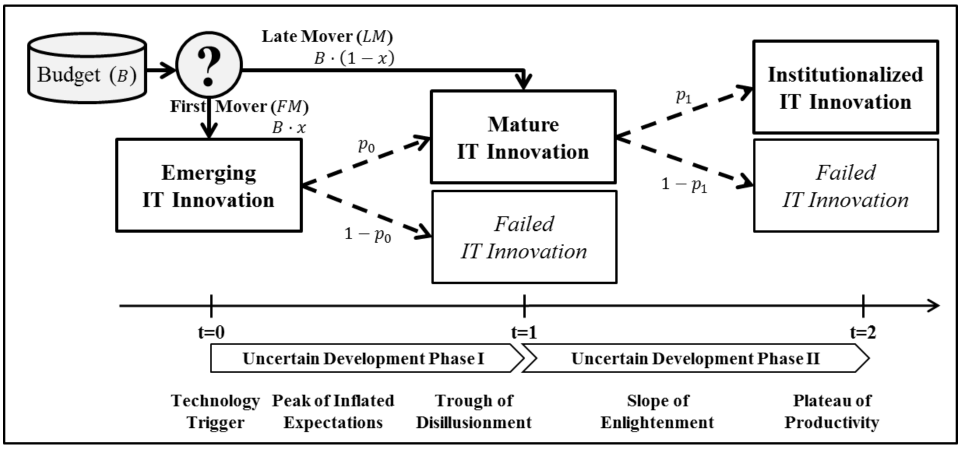


Figure III.3-1 Overview of the model's decision situation

Assumption 3 – Achievable Future Cash Flows

a) Parameters of Cash Flow Functions: *The resulting cash flow $CF_j(ep_j^s, B, x)$ depends on the invested share x of budget B, the budget B itself and the investment's economic potential $ep_j^s \in \mathbb{R}$, $s \in \{uu, ud, d\}$, $j \in \{FM, LM\}$. For the upside scenario ($s = uu$), a FM investment is associated with higher economic potential than a LM investment ($ep_{FM}^{uu} > ep_{LM}^{uu}$). On the other hand, for downside scenarios $s \in \{ud, d\}$, the FM investment's economic potential (ep_{FM}^{ud} and ep_{FM}^{d}) is equal or less than a LM investment (ep_{LM}^{ud}). In addition, the economic potentials for the upside scenario are considerably higher than those for the downside scenarios:*

$$ep_{FM}^{uu} > ep_{LM}^{uu} > ep_{LM}^{ud} \geq ep_{FM}^{ud} = ep_{FM}^{d}. \qquad 1.$$

Economic potentials as IT innovation-specific factors depict the extent of possible long-term returns. They cover the IT innovation's expected market impact according to factors such as consumers' acceptance, market competition, or the probability of easy integration into the company's existing IT infrastructure (Fichman, 2004c; Haner, 2002; Moser, 2011). The factors influence the extent of resulting cash flows and can be estimated through market analyses or internal and external educated guesses by technical experts or those with comprehensive market experience and an appropriate understanding of the emerging innovations´ potential.

If the emerging IT innovation becomes institutionalized in the long run, the investments result in positive cash flows. The highest possible cash flow results from a FM investment since these investments tend to generate higher cash flows for a company owing to FM advantages (Lu and Ramamurthy, 2010; Wang, 2010). Therefore, for the upside scenario, the economic potential of a FM investment (ep_{FM}^{uu}) is higher than that for a LM investment (ep_{LM}^{uu}).

For the downside scenarios, there are three possible cases depicted by our assumption (eq. 1): low positive, zero, or negative cash flows when the IT innovation fails. Thus, the factors covering economic potentials within the cash flow functions are also positive, zero, or negative. First, low positive cash flows are possible if there are no inevitable cash outflows in the future but low cash inflows, for example, if the IT innovation can be partly used or exploited otherwise. Since a FM investment is associated with a deeper engagement in the IT innovation, what impedes a quick switch to another use of the IT innovation, a LM investment enables slightly higher positive cash flows. Second, if no future cash inflows or outflows are possible when the IT innovation fails, this leads to zero cash flows. Thus, the economic potentials are the same: $ep_{LM}^{ud} = ep_{FM}^{ud} = ep_{FM}^{d} = 0$. Third, negative cash flows are possible if future inevitable cash outflows occur, for example, owing to reputational damages or performed organizational changes. Thereby, the cash flows of a FM investment are lower (i.e., more negative) than those for a LM investment due to a longer and deeper engagement. In addition to the described possible cash flows, necessary investment expenditures are also considered in our NPV approach (assumption 5). Thus, even for low positive cash flows, the NPV of the investment can become negative.

b) Course of Cash Flow Functions: *The cash flow $CF_j(ep_j^s, B, x)$ follows a strictly monotonically increasing and concave function.*

A monotonically increasing, concave function is suitable to depict an increasing but diminishing marginal utility according to production theory (Stiglitz, 1993), which is appropriate for cash flows resulting from investments in an emerging IT innovation for several reasons. First, the monotonically increasing course depicts that a higher investment leads to deeper engagement, making deeper understanding and broader implementation possible (Fichman, 2004b; Kimberly, 1981; Melville *et al.*, 2004). Second, a first engagement in an IT innovation enables entering a market or becoming reasonably familiar with a technology (Lu and Ramamurthy, 2010; Stratopoulos and Lim, 2010), and therefore, creates a higher marginal cash flow than an increase in an already high investment, which is depicted by the function’s concavity. Owing to the diminishing marginal utility a pure “more is better” approach might not hold true for every amount of investment since it is possible that at a certain point the marginal investment exceeds the resulting marginal cash flow.

c) Resulting Cash Flows: *Cash flow CF_t^s with $s \in \{uu, ud, d\}$ is the sum of cash inflows and outflows at $t \in \{0; 1; 2\}$, resulting from the FM and LM investment. At $t = 2$, it comprises* *cash flows* $CF_j(ep_j^s, B, x)$ *with* $j \in \{FM, LM\}$ *(Cash flows can be interpreted as the present value at* $t = 2$ *for all possible cash flows generated in the future by the investments):*

$$CF_2^s = CF_{FM}(ep_{FM}^s, B, x) + CF_{LM}(ep_{LM}^s, B, x = 0) - CF_{LM}(ep_{LM}^s, B, x). \qquad 2.$$

Regardless of the point in time, both FM and LM investments belong to the same IT innovation. Therefore, a LM investment reinforces the company's possible FM investment in the IT innovation. As initial investments enable higher marginal cash flows than additional investments, the amount of FM investment, as an initial investment in the emerging IT innovation, must be accounted for when calculating the LM investment's cash flow. Therefore, the cash flow resulting from a LM investment with the invested amount of a FM investment ($CF_{LM}(ep_{LM}^s, B, x)$) is subtracted from the cash flow that would result from a LM investment from the entire budget (i.e., $CF_{LM}(ep_{LM}^s, B, x = 0)$) to calculate the correct cash flow from an investment of the remainder budget as a LM investment (Figure III.3-2).

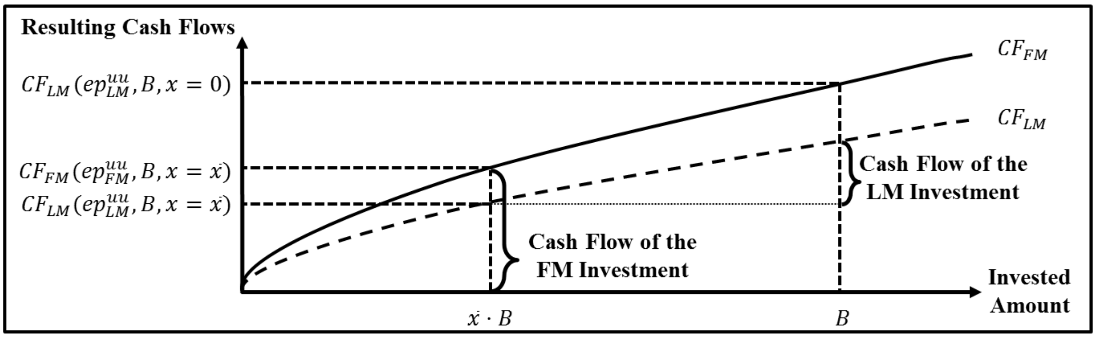


Figure III.3-2 Resulting cash flows in an upside scenario (illustrative)

In addition to the described IT innovation-related specifics, successful engagement in an emerging IT innovation depends on a company's ability to innovate economically and successfully, that is, the company's innovator profile.

Assumption 4 – Innovativeness of the Company

The cash flows resulting from investments in emerging IT innovation for the upside scenario are multiplied by a company-specific factor $i \in \mathbb{R}^+$*, indicating the company's innovator profile.*

The innovator profile i allows us to consider the company's ability to engage in an IT innovation economically, quickly, and efficiently (Swanson and Ramiller, 2004; Fichman, 2004b). If the company is more innovative, it is generally likely to implement the emerging IT innovation more successfully and generate higher cash flows if the IT innovation becomes institutionalized. The innovator profile reflects a company's innovativeness relative to the market's average innovativeness. Thus, for an average innovative company, $i = 1$; for a below average company, $i < 1$; and for an above average one, $i > 1$. Of course, the impact of the innovator profile only applies to the upside scenario, as a company's individual innovativeness does not matter if the IT innovation fails and vanishes from the market.

The company's possible investments and resulting cash flows for the different scenarios with their associated probabilities are presented in Table III.3-1.

Scenario	**Probabilities**	$\boldsymbol{CF_0^s}$	$\boldsymbol{CF_1^s}$	$\boldsymbol{CF_2^s}$
uu	$p_0 \cdot p_1$	$-(x \cdot B)$	$-((1-x) \cdot B)$	$[CF_{FM}(ep_{FM}^{uu}, B, x) + CF_{LM}(ep_{LM}^{uu}, B, x = 0) - CF_{LM}(ep_{LM}^{uu}, B, x)] \cdot i$
ud	$p_0 \cdot (1 - p_1)$	$-(x \cdot B)$	$-((1-x) \cdot B)$	$CF_{FM}\left(ep_{FM}^{ud}, B, x\right) + CF_{LM}\left(ep_{LM}^{ud}, B, x = 0\right) - CF_{LM}\left(ep_{LM}^{ud}, B, x\right)$
d	$(1 - p_0)$	$-(x \cdot B)$	---	$CF_{FM}(ep_{FM}^{d}, B, x)$

Table III.3-1 Possible scenarios with resulting cash flows and associated probabilities

Assumption 5 – Objective Function

The company is a risk-neutral decision maker and aims at maximizing the expected NPV $E[NPV(x)]$ *of the investments in the emerging IT innovation. It is calculated as the sum of expected cash flows* $E[CF_t^s]$ *with* $t \in \{0; 1; 2\}$ *and* $s \in \{uu, ud, d\}$, *discounted with a constant risk-free interest rate* $r \in [0,1]$.

$$\max_{\boldsymbol{x}} \boldsymbol{E[NPV(x)] = CF_0^s + \frac{E[CF_1^s]}{1+r} + \frac{E[CF_2^s]}{(1+r)^2}}\ \boldsymbol{s.t..}\ x \in [0,1];\ s \in \{uu, ud, d\}. \qquad 3.$$

Assume a risk-neutral decision maker is reasonable since investments in new technologies are associated with higher risks than investments that deal with, for example, infrastructure, operational data, and routine processes (Maizlish and Handler, 2005; Ross and Beath, 2002). Therefore, an extensive risk aversion would prevent necessary and useful investments in innovations. The company can maximize the expected NPV by determining the optimal investment strategy indicated by optimal share x^* of the budget ($x = 1$ represents a strict FM strategy, $x = 0$ a strict LM strategy, and $0 < x < 1$ a mixed strategy). A strict FM strategy allows for high cash flows within the upside scenario and bears the risk of rather low or even negative cash flows in the downside scenarios. By contrast, a strict LM strategy possibly results in lower cash flows in the upside scenario or budget saving if the IT innovation is stranded in the first period of development. A mixed strategy, that is, a combination of both strict strategies' chances and risks, possibly leads to a higher expected NPV. The decision is influenced by the amount of strategic budget, success probabilities, and economic potentials of investments regarding the different possible scenarios, and the company's innovator profile.

III.3.4 Model Analysis

In this Section, we analyze the model using exemplary applications and sensitivity analyses. First, we analyze different parameter settings (Table III.3-2) depicting the characteristics of possible real-world scenarios regarding the expected NPV and optimal investment strategy. We then examine the impacts of the input parameters on NPV and optimal investment strategy using sensitivity analyses, by changing the values of one parameter, ceteris paribus (Saltelli *et al.*, 2008). Conclusively we derive further insights and illustrate the connection to the assumptions by computing and analyzing its analytical solution.

Exemplary application

Parameter	B	ep_{FM}^{uu}	ep_{LM}^{uu}	ep_{LM}^{ud}	ep_{FM}^{ud}	ep_{FM}^{d}	i	p_0	p_1	r
Values of baseline scenario	500	1,000	500	0	0	0	1	0.1	0.6	0.1
Lower scenario $(.)\downarrow$	250	500	250	-10	-20	-20	0.5	0.1	0.6	0.1
Upper scenario $(.)\uparrow$	750	1,500	750	20	10	10	1.5	0.1	0.6	0.1

Table III.3-2 Parameter values for the scenario analyses

As functions for the expected cash flows, we use standard root functions as they perfectly cover the characteristic of diminishing marginal cash flows (For example the upside scenario's cash flow at $t = 2$ is: $CF_2^{uu} = [ep_{FM}^{uu} \cdot (B \cdot x)^{0.5} + ep_{LM}^{uu} \cdot (B)^{0.5} - ep_{LM}^{uu} \cdot (B \cdot x)^{0.5}] \cdot i.)$.

Expected NPV and Optimal Solution for Different Scenarios: Applying the parameter values of the baseline scenario, the optimal solution, that is, the optimal ex-ante allocation of budget B to the FM and LM strategy is $x = 0.37$. That is, with an investment of 37% $(x^* \approx 0.37)$ of the budget at $t = 0$ and saving of 63% for an investment at $t = 1$, the company achieves a maximum expected NPV of 677.99 monetary units (Figure III.3-3).

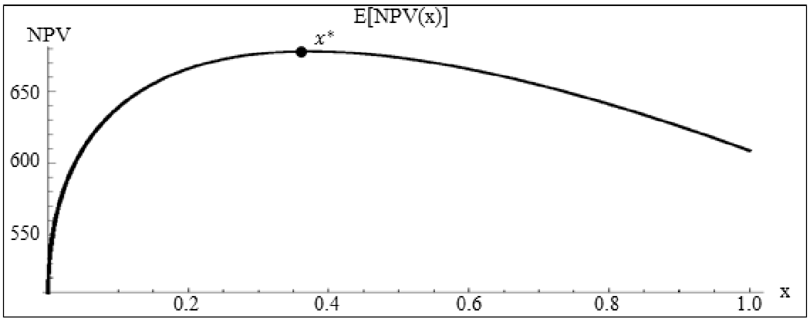
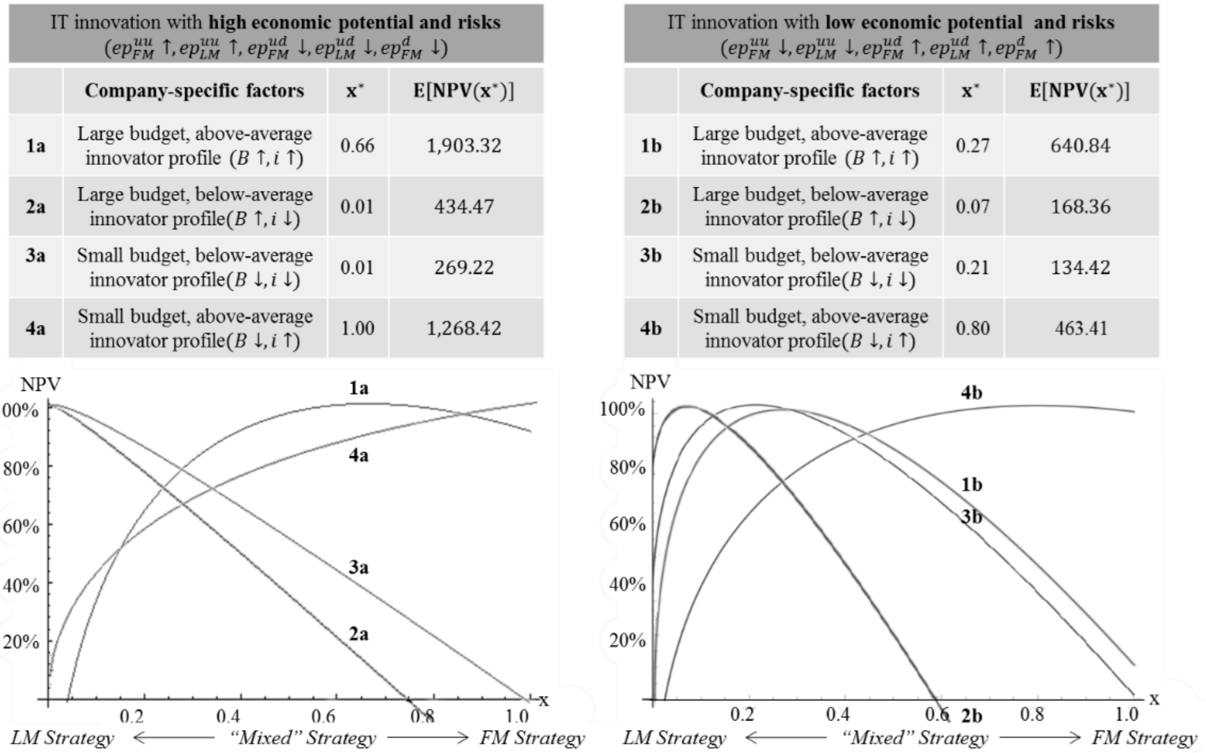


Figure III.3-3 Expected NPV and optimal solution for the baseline scenario

Figure III.3-3 indicates that there is one optimal solution. However, the curve's course indicates that a deviation toward the LM strategy is more critical than that of the FM strategy. Thus, the impact of FM advantages over-compensates the impact of the LM strategy's lower risk, that is, the loss of FM advantages due to the reduced allocation toward the FM strategy is more substantial than the reduction of uncertainty. Moreover, compared to a strict FM or LM investment strategy, it becomes rather obvious that a mixed strategy is advantageous as the expected NPV reaches its maximum value.

Scenario analysis

To further analyze the scenarios, we combine the parameter values of Table III.3-2 that considerably fluctuate around the values of the baseline scenario to cover a broad range of possible scenarios. Since we distinguish between company- and IT innovation-specific input parameters, we combine parameters settings depicting different types of companies and IT innovations. The results are shown in Figure III.3-4.



IT innovation with **high economic potential and risks** ($ep_{FM}^{uu}\uparrow, ep_{LM}^{uu}\uparrow, ep_{FM}^{ud}\downarrow, ep_{LM}^{ud}\downarrow, ep_{FM}^{d}\downarrow$)

	Company-specific factors	**x***	**E[NPV(x*)]**
1a	Large budget, above-average innovator profile ($B\uparrow, i\uparrow$)	0.66	1,903.32
2a	Large budget, below-average innovator profile($B\uparrow, i\downarrow$)	0.01	434.47
3a	Small budget, below-average innovator profile($B\downarrow, i\downarrow$)	0.01	269.22
4a	Small budget, above-average innovator profile($B\downarrow, i\uparrow$)	1.00	1,268.42

IT innovation with **low economic potential and risks** ($ep_{FM}^{uu}\downarrow, ep_{LM}^{uu}\downarrow, ep_{FM}^{ud}\uparrow, ep_{LM}^{ud}\uparrow, ep_{FM}^{d}\uparrow$)

	Company-specific factors	**x***	**E[NPV(x*)]**
1b	Large budget, above-average innovator profile ($B\uparrow, i\uparrow$)	0.27	640.84
2b	Large budget, below-average innovator profile($B\uparrow, i\downarrow$)	0.07	168.36
3b	Small budget, below-average innovator profile($B\downarrow, i\downarrow$)	0.21	134.42
4b	Small budget, above-average innovator profile($B\downarrow, i\uparrow$)	0.80	463.41

Figure III.3-4 Overview of results for different scenarios

Regarding company-specific parameters, we assume a company to have a considerably large or small budget and an innovator profile above or below the market average. Furthermore, by varying the IT innovation's economic potentials as IT innovation-specific factors, we cover two interesting IT innovation-related scenarios. First, the emerging IT innovation seems to be a disruptive technology; that is, on the one hand, an engagement bears the possibility of extraordinarily high returns (depicted by choosing the upper limit values for economic potentials in the upside scenario) if the IT innovation becomes institutionalized. On the other hand, it is characterized by the risk of losing more than the budget (depicted by choosing the lower limit values for economic potential in the downside scenarios) if the IT innovation unsuccessfully vanishes from the market (left part of Figure III.3-4). Second, the IT innovation seems to be a considerable improvement over existing technologies but is not a disruptive technology; that is, on the one hand, it bears the possibility of high, but not exceptional returns (depicted by choosing the lower limit values for economic potentials in the upside scenario) if the IT innovation becomes institutionalized. On the other hand, it is characterized by a lower risk (depicted by choosing the upper limit values for economic potential in the downside scenarios) if the IT innovation unsuccessfully vanishes from the market (right part of Figure III.3-4). The success probabilities do not vary as they are assumed to be average probabilities that depict the average fraction of IT innovations that become institutionalized, regardless of the IT innovation's possible impact. To test the model's sensitivity for different situations, we combine different company- and IT innovation-related settings, resulting in the different decision situations (Figure III.3-4).

For a company with a large budget and above-average innovator profile, the optimal investment strategies x^* (0.66 and 0.27) and the related optimal expected NPVs $E[NPV(x^*)]$ (1,903.32 and 640.84) are rather different. As for the disruptive IT innovation, because of the company's high innovativeness and FM investment's high economic potential for the upside scenario, an allocation of the budget's majority to the FM strategy can be advantageous. Thus, given its high innovativeness, the company can risk acting like a FM to engage in the disruptive IT innovation as it is more likely to be successful and achieve high possible cash flows. In contrast, for the evolutionary IT innovation, a high FM investment is not useful because there are no considerable FM advantages due to the lower economic potential, not even through high innovativeness; therefore, a strategy with focus a on a LM investment is advantageous. However, a higher budget enables deeper engagement and higher cash flows for both IT innovation-specific scenarios compared to the initial situation.

For a company with a large budget but below-average innovativeness, the results significantly differ. Regardless of the IT innovation-specific scenario, the optimal investment strategies x^* (0.01 and 0.07) considerably change toward the LM strategy and the optimal expected NPVs $E[NPV(x^*)]$ (434.47 and 168.36) largely decrease. This shows that below-average companies should rather invest as a LM as they cannot realize the possible FM advantages owing to the lack of knowledge regarding a successful implementation of new technologies.

In addition, the expected NPVs show that even a high budget and optimal investment strategy cannot compensate for the disadvantages of low innovativeness. Moreover, the company must invest carefully as the expected NPVs can even be negative for wrongly chosen FM strategies. In this case, the risk of losing a high budget over-compensates for the possibility of cash flows, which are low owing to the company's inability to successfully adopt new technologies.

Also, changing the budget to a lower limit, indicating a below-average company with few financial funds, compared to the previous scenario, the optimal investment strategy x^* for the disruptive IT innovation is the same (0.01) and marginally changes for the evolutionary IT innovation (0.21). Moreover, the optimal expected NPVs decrease for both types of IT innovations $(269.22$ and $134.42)$ owing to the decreased budget. Because of the low innovativeness, the company should rather invest as a LM, especially in the case of disruptive technologies. For evolutionary IT innovation, the company should not completely rely on a LM strategy; rather, it can risk acting like a FM investor and allocate an appropriate share of the budget to FM investments, since the risk within the downside scenarios is considerably lower than that for disruptive IT innovation. Overall, a company with a low budget and below-average innovativeness can reach positive expected NPVs and does not face a high risk of negative NPVs such as the below-average company with a high budget.

Finally, we continue to assume a company with low available financial funds but with above-average innovativeness. As argued, this depicts the situation start-up companies are faced with, as they regularly have lower financial funds available than traditional companies but are often agile and more innovative. An examination of situation 4a and 4b (s. Figure III.3-4) reveals that optimal investment strategies x^* become almost completely reversed $(1$ and $0.8)$ and the optimal expected NPVs considerably increase $(1{,}268.42$ and $463.41)$ compared to the previous analysis. Hence, for both types of IT innovations, strict FM strategies are advantageous, enabling high expected cash flows. In particular, for investments in disruptive IT innovations, small start-ups can monetize possible FM advantages, investing all available financial funds strictly as a FM (taking the risk of possibly going bankrupt). In addition, even for the evolutionary IT innovation, a FM strategy is advantageous, given the lower risk in the downside scenarios and the positive impact of above-average innovativeness on the expected cash flows. Thus, the innovativeness of a company has a considerable positive impact on the optimal investment strategy and expected NPV, even if the company does not have substantial financial resources at its disposal.

Model analysis conclusions

From the analyses of the initial scenario and different company- and IT innovation-specific scenarios, we draw the following conclusions:

- a below-average innovative company should rather choose a LM strategy;
- an above-average innovative company should rather choose a FM strategy, except if it has a large budget at its disposal and the IT innovation is evolutionary;
- a company with a large budget at its disposal should rather choose a LM strategy, except if it is above-average innovative and the IT innovation is a disruptive one;
- a company with a small budget at its disposal should rather choose a FM strategy if it is above-average innovative and a LM strategy if it is below average;
- as for expected NPV, the impact of the company’s innovativeness is stronger than that of the budget; and
- for evolutionary IT innovations, a LM strategy is advantageous, except if the company has a small budget at its disposal and is above average innovative.

Also, the analyses indicate that the optimal investment strategy and the resulting expected NPVs are rather sensitive to different scenarios. Therefore, for the decision regarding the optimal investment strategy, a mindful consideration of company- and IT innovation-specific factors is inevitable.

To enable a better understanding of how the amount of budget influences the decision, we analyzed its isolated impact on the optimal strategy and expected NPV. For the sensitivity analyses, based on the baseline scenario, we show an alteration of the parameter value for budget B. As depicted on the left-hand side of Figure III.3-5, a higher budget leads to a higher expected NPV and a decreasing share allocated to the FM investment (right-hand side of Figure III.3-5).

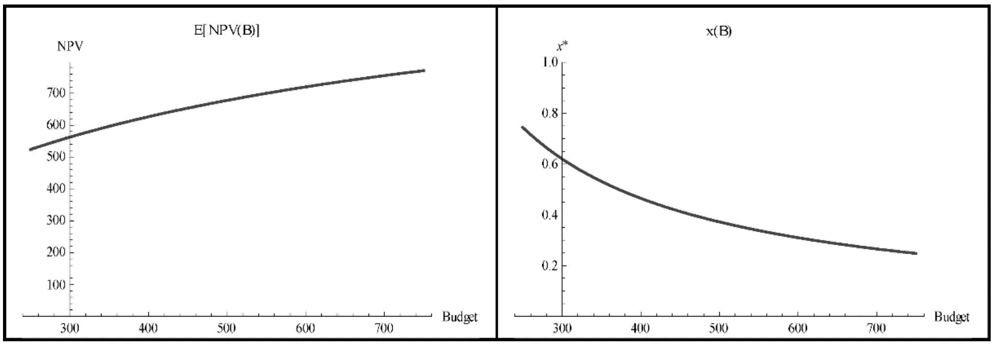


Figure III.3-5 Influence of budget on expected NPV and optimal solution

The concave increase of the expected NPV demonstrates the cash flows' characteristic of diminishing marginal cash flow; that is, the achievable additional marginal cash flows decrease with an increase in the invested budget. Interestingly, the decreasing allocation to the FM investment indicates that a company with higher financial funds can afford to wait longer, observe the emerging IT innovation's development, and act more as a LM investor. As the budget increases in absolute value, it is possible to save a higher share of the budget for a LM investment without a considerable reduction of the FM investment's amount. Moreover, a company with low available funds would rather invest as a FM investor to maintain the possibility of high cash flows owing to FM advantages.

To derive further insights and illustrate the connection to the assumptions we specified the objective function by inserting all the parameters for different possible scenarios and computed the first derivation of the objective function with respect to x. In sum we can state that for an optimal solution, the risk and return profiles of both investment strategies have to be balanced. Furthermore, increasing one of the economic potential factors of the FM or LM investment strategy should increase the budget share allocated to the respective strategy. An increase in the success probabilities (separately or together) should increase the budget share allocated to the FM strategy; and an increased innovator profile should increase the budget share allocated to the FM strategy.

III.3.5 Conclusions, Limitations, and Suggestions

Decisions regarding a strategy for investments in an emerging IT innovation are often not based on economically well-founded evaluations and analyses, as the market for IT innovations is characterized by intense competition, unclear impacts, and an environment influenced by the hype surrounding an emerging IT innovation. In this context, research can provide valuable insights into the ex-ante determination of optimal investment strategies using quantitative models. In addition to studies analyzing the optimal allocation of recurring IT innovation budgets, it is important to investigate factors affecting decisions regarding optimal strategies for investments in a given emerging IT innovation. To provide insights into causal relationships and analyze key factors, we consider relevant specifics of the company (e.g., budget and innovator profile) and IT innovation (e.g., success probabilities and economic potential) within our quantitative optimization model. By considering these factors, we contribute to central research questions in IT innovation theory, that is, *when* and *to what extent* should a company invest in an emerging IT innovation (Swanson and Ramiller, 2004). As for company-specific factors, first, our analyses show that the amount of available budget positively impacts expected NPV (a higher budget enables higher investments). Second, a higher budget offers a company the opportunity to defer an investment and first observe the IT innovation’s development. Therefore, a company with sufficient financial funds does not need to invest its entire budget immediately. Third, the most relevant factor for successful engagement in an emerging IT innovation is the innovativeness of the company. Fourth, broad knowledge and experience regarding how to successfully innovate enables a company to engage in an emerging IT innovation at an early stage and monetize possible FM advantages. Thus, the expected NPV considerably increases, which emphasizes steady organizational learning to improve and maintain a company’s innovativeness (Häckel *et al.*, 2017). Fifth, our analyses show that even with low financial funds, a remarkable expected NPV can be achieved if the company’s ability to innovate is above average. IT innovation-specific factors elucidate that first, for investments in an emerging IT innovation that seems rather evolutionary, a LM strategy is almost always the appropriate investment strategy. Even in this case, a highly innovative company with a low budget should choose a strict FM strategy to monetize FM advantages. Second, far more interesting are rather disruptive emerging IT innovations. Thus, company-specific characteristic, particularly the company’s innovativeness, mainly determine the respective optimal strategy and therefore, the risk a company should take. By applying our model to allocate an investment budget, we see that it is advantageous to invest part of our innovation budget in emerging IT innovations, which essentially corresponds to earlier qualitative and empirical studies by Wang (2010), Lu and Ramamurthy (2010) or Dos Santos and Pfeffers (1995). These showed that investments in emerging IT innovations lead to improved company performance. On the other hand, our results show that a LM strategy is meaningful for a below-average innovative company, which supports findings from Hoppe (2000), stating that a LM strategy advantageous, e.g. in the case of a low success probability for an emerging innovation. To reinforce the model’s validity and our conclusions, further research in a given organizational context or using empirical data might be valuable (Hevner et al., 2004; Wacker, 1998). Furthermore, our model and its findings may not be practically applicable without adjustments. For example, investments are often not infinitely divisible. Thus, in reality, a possible investment strategy closest to the theoretically optimal solution would have to be chosen. Moreover, further research focusing on some of the limiting aspects might be useful. In particular, the determination of input parameters using empirical and benchmark analyses or educated assessments using experts or consultants and a subsequent analyzation by deep learning methods such as Genetic Algorithm or Neural network algorithm to ensure an expedient data basis could be helpful. A further promising direction for future research could be the development of an integrated portfolio approach that comprehensively depicts investments in different emerging IT innovations. To analyze effects of the real world more precisely, a dynamic multi-period model might be valuable. Such a model could e.g. consider learning effects that reflect the experience a company can gain by a steady and continuous engagement in IT innovations. Despite the model's limitations which offer possibilities for future research, our results and the theoretically sound economic approach contribute to improving a company's decision and further development of a quantitative theory regarding investments in emerging IT innovations.

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IV Analysis of Specific IT Innovations

The first research paper P5 in this Chapter "*Structuring the Anticipated Benefits of the Fourth Industrial Revolution*" (Section IV.1) examines the anticipated benefits of technologies and innovations in the context of Industry 4.0 (e.g., cyber physical systems and smart factory). It presents a structured overview of 24 conclusive benefits clustered in four dimensions. Further, managerial implications and challenges are discussed.

The second research paper P6 *"Creating Competitive Advantage in E-Business Value Chains by Using Excess Capacity via IT-enabled Marketplaces"* (Section IV.2) analyzes the potential of using the IT-enabled concept of excess capacity markets (ECM) for business process service providers (BPSP). The analysis is conducted by means of an analytical model based on queuing theory and evaluates it through a discrete-event simulation applying a possible application scenario.

IV.1 Research Paper 5: "Structuring the Anticipated Benefits of the Fourth Industrial Revolution"

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Abstract: *The digitalization of production facilities and the accompanying changes are anticipated to transform entire industries posing a fierce pressure on companies to deal with these developments regarding their information technology management. To lay the foundation for the development of corresponding business strategies, we structure benefits of Industry 4.0 through a structured literature review and categorize them using an established framework for IS benefits. Benefits for companies arise within four dimensions and concern various issues ranging from production related benefits to superordinate benefits affecting the business model. To conclude, managerial implications resulting from dependencies and the variety of benefits are presented.*

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[1] The affiliations of Annabelle Geißler and Jochen Übelhör have been updated because they changed their jobs after the publication of the paper. At the time of creation of the paper, both affiliations have been FIM Research Center.

IV.1.1 Introduction

In the recent past, there has been a tremendous hype built up around *Industry 4.0*. The term comprises technological developments such as Internet-of-Things (IoT), Internet-of-Services, or cyber physical systems (CPS) (Lasi et al. 2014). In this paper, we focus on CPS as a representative of Industry 4.0, the implementation of smart factory concepts and their anticipated benefits. As *Industry 4.0* is a terminology particular common in Germany and in absence of a common global terminology, we explicitly include related concepts such as *Industrial Internet*, *Smart Manufacturing*, or *Advanced Manufacturing* that are common in English-speaking countries. In our understanding, Industry 4.0 comprises in its inner kernel the advanced digitalization of production facilities through the digital connection of smart machines and products with networked embedded systems and the extensive integration of information systems, digital services, and Internet-based technologies (Barrett et al. 2015; Schuh et al. 2014b; Zuehlke 2010). These promise great potentials and benefits for industrial applications as smart products are envisioned to self-control their manufacturing process and smart factories are anticipated to self-optimize production processes in real-time and respond context-specific to turbulences in production and to fast changing customer demands (Schuh et al. 2014b). Besides others, these capabilities increase efficiency and competitiveness as they enable the flexible production of highly customized products at costs comparable to mass production (Radziwon et al. 2014). Further, innovative digital business models like predictive maintenance or pay-per-use concepts utilize the tremendous amount of generated production and product data and enable innovative products enhanced with digital services (Lasi et al. 2014).

These developments are anticipated to deeply impact existing business strategies and success models and transform whole economies in a disruptive manner (Iansiti and Lakhani 2014). Therefore, companies in all industries face a fierce pressure to deal with the fundamental changes and rethink their strategies regarding investments in Industry 4.0 technologies to retain competitiveness (Geisberger and Broy 2015). Otherwise, increasing efficiency of competitors, market entries of non-traditional competitors, and new digital business models intensify competition and, ultimately, jeopardize companies that fail to undergo the necessary transformation process. Accordingly, companies must not only evaluate whether to invest into Industry 4.0, but especially into which specific technologies and in which order. To come to these crucial strategic decisions in correspondence with value-based management principles, investments have to be evaluated ex-ante under consideration of involved costs, risks, and benefits (Faisst and Buhl 2005). While costs and risks have already been researched quite extensively, benefits of Industry 4.0 have not yet been investigated in a structured manner. Till date, authors only point out benefits for motivational reasons or evaluate highly specific and application-dependent benefits. To the best of our knowledge, there is no comprehensive picture of Industry 4.0 technologies and their contribution to value creation. Consequently, the evaluation of benefits remains a major obstacle as the variety and complexity of technologies and the absence of best-practices or industry standards complicate their identification and quantification. However, this would be necessary to ensure a holistic view on Industry 4.0 business strategies. To close this gap, our research focuses on benefits of Industry 4.0 and addresses the following research question:

RQ: *Which benefits of Industry 4.0 are anticipated in scientific literature?*

By identifying benefits based on a structured review of scientific literature and by categorizing them into a structured benefits framework, we provide a comprehensive overview of the benefits of Industry 4.0. This helps to better describe the characteristics of Industry 4.0 technologies that are associated with value creation. Further, our research represents an essential first step towards the comprehensive evaluation of smart manufacturing technologies and lays the ground for a subsequent identification and quantification of benefits. The remainder of our paper is organized as follows: We outline our methodology in Section IV.1.2. Section IV.1.3 provides a review on the investigated literature. Section IV.1.4 presents the identified benefits and a categorization of these benefits into an IS benefits framework. Section IV.1.5 contains a discussion of managerial implications, before Section IV.1.6 presents a conclusion and gives an outlook on further research.

IV.1.2 Research Methodology

As Industry 4.0 is a quite young field of research and the body of corresponding literature on benefits of Industry 4.0 is rather limited, the aim of our research is not the synthesis of research on benefits, but a methodically sound identification of respective benefits mentioned in scientific literature. For the approach conducted in this research, the methods presented by Bandara et al. (2011), Fettke (2006), vom Brocke et al. (2009), and Webster and Watson (2002) concerning structured literature reviews in the IS field serve as a basis. Although the approaches coincide in their basic structure (e.g., all authors incorporate a literature search comprising keyword search in databases), they differ regarding their exact research procedure and purpose. Therefore, we combine the approaches and derive four steps: Subsequent to a literature search (1), relevant articles are identified (2) and analyzed (3). Afterwards, the results are structured (4).

Step 1 - Search process: Since the investigated topic is an emerging field and concerns various disciplines, a concept-centric literature search is executed (Webster and Watson 2002). To query a wide selection of journals and to include conference proceedings, we query databases listed in Table IV.1-1 with search terms for Industry 4.0 and related concepts (i.e. *Industry 4.0*, *Internet-of-Things*, or *smart manufacturing*) in combination with terms that ensure results with a strong association industrial applications (i.e. *production*, *manufacturing*, or *factory*). The keyword search is conducted in the search fields abstract, title, and keywords as this search strategy is supposed to render papers focusing on the target topic (Bandara et al. 2011). The search strategy renders a total of 177 results.

Databases	ScienceDirect, EbscoHost, ProQuest, AIS eLibrary
Search Fields	Title, Abstract, Keyword
Source Types	Journals, Conferences
Search Terms	(Industry 4.0 OR Industrie 4.0 OR Internet of Things OR Industrial Internet OR Cyber Physical System OR Cyber Physical Production System OR Smart Factory OR Smart manufacturing) AND (production OR manufacturing OR factory OR Produktion OR Fabrik OR Industrie)

Table IV.1-1 Parameters of Keyword Search

Step 2 - Selection of relevant literature: As vom Brocke et al. (2009) argue, the limitation of the amount of literature by keyword search should be content-based and include analyzing titles, abstracts and full texts. Accordingly, titles of all articles are examined to exclude articles not dealing with Industry 4.0 or dealing with non-industrial applications. Further, all articles in other languages than English or German are excluded. Then, abstracts of the remaining articles are analyzed to select those discussing Industry 4.0. In a last step, full texts of the remaining articles are screened by examining relevance for Industry 4.0 and if benefits of Industry 4.0 are mentioned in the article. This results in 57 articles (55 in English and 2 in German) relevant for further analysis. 27 articles are published in conference proceedings from different fields like production engineering, or computer sciences. The other 30 articles were published in journals from different fields ranging from engineering and computer sciences to management sciences.

Step 3 - Analysis of relevant literature: 57 publications are analyzed for mentioned benefits of Industry 4.0. Thereby, we define *benefit* as an umbrella term for positive effects like opportunities, potentials, value, or improvements for companies achieved through the implementation of Industry 4.0 technologies. Thus, macro-economic effects for economies are not considered. Thus, we subsume different levels of benefits, i.e. different degrees of concretization, under one term. This approach seems reasonable as Industry 4.0 is a young and emerging field of research and, so far, the vast majority of benefits remain rather vague potentials with no empirical evidence in literature. Each benefit mentioned and the respective publication are recorded in a database resulting in an initial list of multiple benefits. After consolidating the initial list and removing doubles and highly similar benefits, we obtain a list of 365 benefits.

Step 4 - Synthesis of analysis results: There are different frameworks for structuring benefits. For instance, DeLone and McLean (1992) provide a framework with six dimensions regarding aspects of IS and Abelein et al. (2009) develop a framework consisting of technical, organizational, and strategic business dimensions. An established framework for IS benefits proposed by Anthony (1965) structures benefits into the three dimensions *operational*, *managerial*, and *strategic* as this allows the distinction of benefits regarding the hierarchical levels of decision-making in organizations, i.e. *operational control*, *managerial control*, and *strategic planning*. Since we aim to provide the basis for the analysis of individual use cases and concrete decisions, we regard Anthony’s (1965) framework as most suitable. This classification supports the differentiation of the impact of benefits and, thus, facilitates their subsequent in-detail evaluation and quantification. Numerous authors applied an extended version of Anthony’s three dimensional framework by adding the dimensions *organizational* and *information technology (IT) infrastructure* (e.g. Shang and Seddon 2000, Shang and Seddon 2002; Wang et al. 2016) as it was discovered that certain IT benefits could not (unambiguously) be clustered without them, in example organizational benefits in terms of improved focus, cohesion, learning and execution were identified (Shang and Seddon 2002). However, as we view advancements of IT as core enabler of Industry 4.0, we refrain from gathering benefits describing enhancements of IT and do not include *IT infrastructure* in our framework. Additionally, IT is developing at an increasingly pace, so the inclusion of corresponding benefits would impair the framework's long-term relevance.

Each benefit is assigned to one of the four dimensions. Nevertheless, there are interdependencies between the dimensions that are addressed later in this paper. To ensure objectivity, the benefit assignment is done by two researchers separately and merged while assignment differences are discussed. In a second step, benefits within each dimension are clustered, again by two researchers separately, and matched to consolidated benefits. Finally, we obtain our benefits framework as the central artefact of our research: a structured representation of Industry 4.0 benefits. The framework is evaluated by a discussion with ten other researchers and the results of the evaluation are considered in the further development of the framework presented in Section IV.1.4.

IV.1.3 Overview of the Investigated Literature

In the following, we give an overview on the examined scientific literature concerning Industry 4.0 from different fields of research like engineering, operations research or sustainability. Due to the innovative nature, many authors approach Industry 4.0 in a general manner, propose definitions, and discuss the state of technologies and future research and development challenges. For example, Mikusz and Csiszar (2015) develop a framework to examine characteristics and abilities of a CPS application in industrial robotics. Wang et al. (2015) outline characteristics and definitions of CPS and present advancements in CPPS to point towards research directions. Other authors focus on risks and opportunities of smart manufacturing (Banham 2015), review the term *smart* in relation to technology, and propose a definition for smart factories (Radziwon et al. 2014). However, due to a macro-perspective view on Industry 4.0, these approaches make only general statements on benefits of industry 4.0 in the context of new business models.

Despite these general approaches, there are publications addressing specific topics accompanying Industry 4.0 and related concepts. For example, some investigate architectures or models for the integration of CPS/CPPS in manufacturing and the realization of smart factories (Bagheri et al. 2015; Majstorovic et al. 2015). Other authors like Wright (2014) outline the effects of CPPS regarding products or focus on effects for humans in smart manufacturing environments (Dombrowski and Wagner 2014). An issue examined by several authors concerns production and process management (Denkena et al. 2014; Reischauer and Schober 2015; Seitz and Nyhuis 2015). For example, Seitz and Nyhuis (2015) present advantages of CPS for production planning, controlling, and monitoring. A different stream of literature deals with the implication for supply chains (Frazzon et al. 2015; Papazoglou et al. 2015; Veza et al. 2015). A reference architecture for smart manufacturing networks is developed by Papazoglou et al. (2015), while Veza et al. (2015) propose a management approach for smart factory networks. Laboratory research facilities are another topic discussed (Faller and Feldmüller 2015; Hummel et al. 2015; Schuh et al. 2015a; Weyer et al. 2015; Zuehlke 2010). For instance, Hummel et al. (2015) point towards the importance of learning factories for the qualification and training of professionals. Moreover, several different topics are discussed such as the collection and processing of data, data analytics, and simulations (Barthelmey et al. 2014; Lee et al. 2014; Neuböck and Schrefl 2015; Rosen et al. 2015), the development of new business models (Rudtsch et al. 2014), collaboration mechanisms (Schuh et al. 2014b; Schuh et al. 2015b), service innovations (Hertrich et al. 2015) or lean production principles (Kohlberg and Zuehlke 2015). These approaches give explicit examples for benefits, however, due to the specific research context, they are only partially applicable for the comprehensive evaluation of the strategic use of Industry 4.0.

Based on this diverse body of scientific literature, we can conclude that scientific literature mentioning benefits of Industry 4.0 and related concepts differs in focus and scope and deals with various aspects of these concepts. Despite the variety of different approaches, to the best of our knowledge, there is no structured framework that provides practitioners with a comprehensive overview of potential benefits. Therefore, we aim to contribute to this research gap by proposing a structured benefits framework to enable decision makers to identify relevant fields of actions for their digitalization strategy and to evaluate potential benefit dimensions from the realization of Industry 4.0 investments and their contribution to value creation in organizations.

IV.1.4 Categorizing the Benefits of Industry 4.0

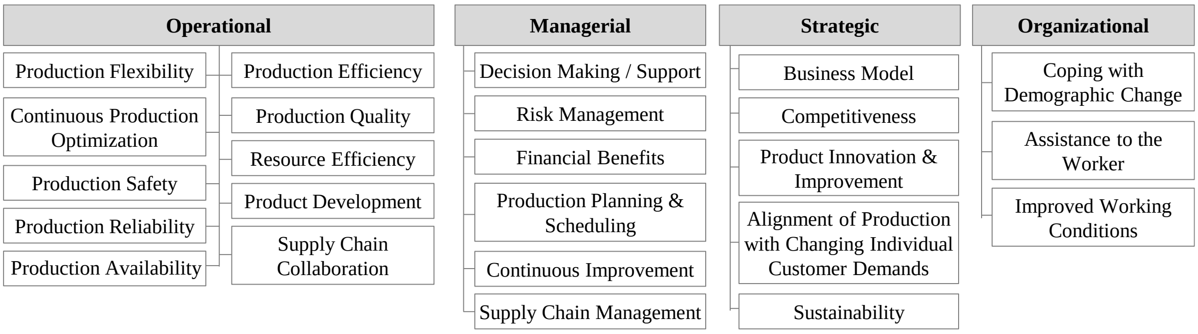

Figure IV.1-1 Benefits framework for Industry 4.0

In the following, we present our benefits framework for Industry 4.0 that is based on an IS benefits framework as it provides predefined dimensions for the consolidation and categorization of the extensive list of identified benefits. Further, the framework is designed for managers to support the assessment of benefits and, therefore, is appropriate for the categorization of benefits considering practitioners' needs regarding organizational decision-making and strategy development. As mentioned in Section IV.1.2, the applied framework comprises *operational*, *managerial*, *strategic*, and *organizational* benefits. Operational benefits contain benefits concerning periodically repeated actions and improvements of practical tasks (Shang and Seddon 2002), while managerial benefits refer to benefits resulting from a better supply of information facilitating advances in the resource allocation and control, operation monitoring and support of strategic business decisions (Shang and Seddon 2002). Benefits affecting long-term planning and high-level decisions are referred to as strategic benefits (Shang and Seddon 2002). Further, organizational benefits involve overarching goals such as focus, learning, and execution within organizations (Shang and Seddon 2002). The benefits are allocated to one of the four dimensions. Since many benefits address same or related issues, similar benefits are consolidated and clustered within the respective dimensions. Figure IV.1-1 shows our benefits framework for Industry 4.0 comprising benefits anticipated in scientific literature. As each benefit is a condensate of several benefits from scientific literature, we provide detailed insights into related concepts of each benefit in tables Table IV.1-2 to Table IV.1-5 and indicate the number of articles within our final paper sample in which a benefit was mentioned. However, the number of articles is only informative and does not allow an assessment of the significance of a benefit.

Benefits assigned to the *operational dimension* of our framework are primarily production related. For instance, *continuous production optimization* refers to the capability of smart factories to (self-) optimize the production system or production processes. Thereby, Industry 4.0 technologies allow the optimization regarding various goals and business metrics as stated by Weyer at al. (2015) and Kolberg and Zuehlke (2015). Another concept widely discussed is *production flexibility*. While in some cases, flexibility is not further expanded on, in some publications it is associated to modularity and reconfigurability of production systems and processes through plug-and-play principles. Veza et al. (2015) present a different perspective, pointing towards the flexibility in terms of short-term responsiveness in case of disruptions. Further related concepts are adaptability, agility, and variability. Another aspect of production expected to benefit from Industry 4.0 is production quality. The anticipated benefits are mainly a reduction of reworking or scrap. Wright (2014) for instance states that wireless sensors can guarantee that final products are completely manufactured. Further, *production reliability* is supposed to benefit from Industry 4.0 including robustness, resilience, and the handling of unprecedented events enabling production systems to reduce potential human error (Banham 2015) and to autonomously improve or maintain a status by self-diagnosis technologies (Mönks et al. 2016). A special case of reliability is production availability discussed extensively in literature and referring to a reduction of downtime and a higher usability of intelligent factories.

Benefit	Related Concept
production flexibility [24]	i.a. flexibility, adaptability, and reconfigurability of production systems; modularity of production modules; easing of engineering and set up; flexibility during technical modification; less time consumption during commissioning; no engineering efforts for reconfiguration; high process variability; adaptability to new product variants or production systems
continuous production optimization [26]	i.a. optimization of production; of production systems and processes; enhanced equipment efficiency; compensation of limited manufacturing capabilities; self-optimization of production systems; enhanced production capabilities
production safety [8]	i.a. higher safety; safer asset utilization; reduction of safety incidents
production reliability [23]	i.a. high reliability; robustness; resilience; handling of unprecedented events; flexibility to respond to disruptions and failures in real-time; autonomous problem handing and reaction to maintain the system's status
production availability [4]	i.a. increased/high availability; reduction of machine downtime; usability of intelligent factories
production efficiency [33]	i.a. improved production efficiency; more efficient asset utilization; just-in-time proceeding of goods; efficient transportation; increased service efficiency; increase of throughput; faster production ramp-up; improved technical support and maintenance; improved quality control
production quality [10]	i.a. fewer product defects; reduction of reworking; lowering of scrap and failures; quality improvement
resource efficiency [15]	i.a. energy savings; less energy consumption; resource efficient production; optimal resource consumption; reduction of material and supply usage; reduction of waste; gains in material efficiency
product development [7]	i.a. innovative product development; accelerated development processes; flexible product development; better quality of development; reduction of number of iterations between product designers and process planners
supply chain collaboration [4]	i.a. increase of collaboration productivity; higher supply chain productivity; higher agility and integration of complete supply chain; improved overall performance of supply chains in terms of service-level and flexibility; increase of logistic performance

Table IV.1-2 Operational Benefits of Industry 4.0

Further, an increase of *production safety* is expected including higher safety of machines and the reduction of safety incidents. Another operational benefit is *production efficiency*. While some authors mention general efficiency gains in relation to production or asset utilization, others, anticipating more specifically, for instance, a promotion of just-in-time manufacturing. One concept in regard to production efficiency is a better technical support of machinery and plant equipment. Rudtsch et al. (2014) describe the concept of remote maintenance that will support maintenance processes through web-based technologies and IoT. Further operational benefits not directly affecting the shop floor are *resource efficiency* and *product development*. Resource efficiency is addressed in some cases in general, but also more specific in regard to energy efficiency in terms of a lower energy consumption or energy savings. Similarly, general benefits regarding resources are expected to materialize through a more accurate resource deployment, which is also reflected in waste reduction and a lower overall consumption of resources. In addition to the production of products, benefits are also anticipated for product development. As Rosen et al. (2015) argue, ubiquitous connectivity will close the digitalization loop and enable optimized product design cycles. Further, Schuh et al. (2014a) state that simulation and virtualization will enable accelerated development processes. Thereby, virtualized development processes contribute to *resource efficiency* through reduced material usage. Contemplating a network of firms, another operational benefit is improved *supply chain collaboration* as higher collaboration productivity through improved information sharing and increased IS integration across company-boundaries within the eco system is one core characteristic of Industry 4.0.

Managerial benefits comprise - similar to the operational level - benefits directly related to production as well as benefits not related to production. There, the benefit *production planning & scheduling* subsumes the optimization of production management and planning, of maintenance scheduling, and of inventory management as well as efficient and advanced planning processes. Schuh et al. (2015b) outline that an improved cooperation within a network of firms enables improved forecasting and advanced and efficient planning processes and, thus, facilitate to counteract over-production as a result of bullwhip-effects. Further, *continuous improvement* enabled by increasing transparency through improved data acquisition and analysis affects production as it concerns effective and efficient process and performance improvement. For instance, Kolberg and Zuehlke (2015) elaborate on Industry 4.0 technologies and their application in regard to lean production principles and conclude that innovative automation technology is a promising topic. While benefits regarding *decision making / support* might concern production, they are not limited to it. Yang et al. (2016) state that real-time information about positioning and working status might assist decisions concerning production and inventory management. Schuh et al. (2015b) further argue that enabling a higher transparency within the supply chain contribute to comprehensibility and, thus, sustainability of decisions and their effects. Benefits not directly linked to production concern *risk management*. While Majstorovic et al. (2015) and Davis et al. (2012) address risk management without presenting more details on how Industry 4.0 is supposed to assist, Banham (2015) discusses the reduction of risk at length, arguing that overall strategic, operational and financial risks are reduced. For instance, the increased flexibility of production systems reduces both strategic risks in regard to fast changing customer demands and operational risks in regard to lengthy technical modifications, while improved product development reduces product failure risks and, thus, financial risks. Benefits concerning positive financial aspects are summarized as *financial benefits* resulting from various aspects like effects on the shop floor. For example, Bagheri et al. (2015) refer to significant economic potential of Industry 4.0 enhanced factories. Similar to the operational dimension, benefits regarding *supply chain management* also exist in the managerial dimension, for instance, in regard to shared information management, risk management or general optimization. Indeed, managerial benefits are more divers including a better handling of complexity, security for single parts of a supply chain, and a better level of information sharing.

Benefit	Related Concept
decision making / support [11]	i.a. effective and efficient decision making; improved decision support; improved performance monitoring in distributed manufacturing; real-time reaction on problems in production
risk management [4]	i.a. improved risk prediction, planning, and management; reduction of strategic, operational, and financial risk
financial benefits [4]	i.a. economic potential; improvement of working capital; radical performance improvement
production planning & scheduling [15]	i.a. efficient and advanced planning process; optimization of manufacturing management, maintenance, and service scheduling; optimal production planning and inventory management; adaptive production scheduling; reduced planning costs
continuous improvement [4]	i.a. effective and efficient process improvement; continuous improvement processes; enhancing existing lean production solutions and extending their applicability; improvement of overall performance and maintenance management; continuous improvement of manufacturing processes; higher quality of processes; improvement of quality of production
supply chain management [4]	i.a. dynamic management of complex environments with short-lived supply chains; security for all supply chain's elements, access to data, knowledge about demand/stock/sales/prediction of anomalies; optimization of value chain by implementation of autonomously controlled and dynamic production; solving problem of complexity in supply chains

Table IV.1-3 Managerial Benefits of Industry 4.0

Strategic benefits comprise abilities by generating new *business models*, enabling *product improvement and innovation*, and the *alignment of production with changing, individual customer demands* as well as an enhancement of *competitiveness* and *sustainability*. Further, new *business models* become feasible. While some authors make rather general statements on new opportunities for value-creation, Veza et al. (2015) and Mikusz and Csiszar (2015) give explicit examples arguing that new business models emerge in form of complementary or additional services. According to Mikusz and Csiszar (2015), new business models facilitated by networked CPS within production facilities and the availability of real-time information are *Add-On*, *Product as a Point of Sales*, *Object Self-Service*, and *Lock-in* business models. Veza et al. (2015) state that new business models appear in the form of *Manufacturing-as-a-Service*, *Industrial Product-Service Systems*, or comparable. Regarding *product innovation and improvement*, benefits include the enhancement of product performance, its design, quality, and sustainability as well as additional digital services, and shorter innovation cycles. For example, Davis et al. (2012) argue that new innovative products are facilitated by increased workforce and manufacturing innovation. Another benefit is the *alignment of production with changing, individual customer demands*. It refers to the efficient production of individualized products in variable volumes, i.e., mass customization (Dombrowski and Wagner 2014). Further, higher customer satisfaction and an increased flexibility for changing customer demand are expected. *Competitiveness* includes, besides an increased competitiveness in general, benefits regarding cost and profit (contributing to financial benefits), market responsiveness, and a shorter time-to-market. For instance, Schuh et al. (2014b) and Davis et al. (2012) state that costs per unit decrease and higher profits can be achieved through shorter time-to-market. *Sustainability*, considered indispensable for a company's long-term success (Perrot 2015), is another benefit that also contributes to resource efficiency on the operational level. While benefits addressing sustainability in general are mentioned in some publications, others address ecologic sustainability specifically. For instance, Schuh et al. (2015b) elaborate on how Industry 4.0 ultimately enhances ecological sustainability.

Benefit	Related Concept
business model [6]	i.a. innovative business models; improved or novel business processes within value creation along product life cycle; new market opportunities; new value-creation opportunities
Competitiveness [13]	i.a. increased competitiveness; maintain competitiveness through mass customization; production of individual products at reasonable cost; lower cost per piece; reduction of cost pressure; reduction of pressure regarding demands for individualized products; improvement of time-to-market; improved ability to respond to varying market demands
product innovation & improvement [18]	i.a. individualization of products; innovative, complementary products and services; enhancement of product design and in-product services; additional customer-value on use; extension of products with digital services; improvement of next product generations; distribution of product information to customer; reduction of product failure risk
alignment of production to changing, individual customer demands [17]	i.a. product individualization; mass customization; lot size one; optimized product customization; increased customer satisfaction; rapid response to changing customer needs and individual customer requirements; alignment of manufacturing with customer demand through flexible production
Sustainability [5]	i.a. maximizing environmental sustainability; benefits for sustainability; improved processes sustainability; sustainable practices

Table IV.1-4 Strategic Benefits of Industry 4.0

In the *organizational dimension*, *assistance of the worker* is expected to benefit from Industry 4.0 by new ways of support, for example, through advanced gathering, processing, and visualization of process date (Schuh et al. 2015a) and virtual instructions at the point of action through smart devices (Weyer et al. 2015). Further, working conditions are expected to ameliorate through novel tasks, human-centric production systems, and health related issues. Rudtsch et al. (2014) mention that human-centered production processes enable production processes to follow human speed and instruction. Moreover, decoupling the place of work from the location of the worker by wireless technology will increase the mobility of humans in production. Further, coping with demographic change constitutes the third organizational benefit as Industry 4.0 technologies can contribute to less burdening work systems (Hummel et al. 2015).

Benefit	Related Concept
coping with demographic change [1]	i.a. less burdening work systems to cope with intensifying demographic change
assistance to the worker [4]	i.a. context-aware assistance to people and machines in task execution; task simplification; new ways of gathering, processing, and visualization process data; virtual instructions and sensor-based monitoring
improved working conditions [7]	i.a. improved health, better working environment; assistance towards more productive, less burdening work; decoupling of workplace from physical location of worker; human-centered production processes regarding speed and instructions; adjustment to human workforce

Table IV.1-5 Organizational Benefits of Industry 4.0

IV.1.5 Managerial Implications and Challenges

In the following, we discuss managerial implications and challenges gained in the course of our research that should be considered in the strategic alignment of companies in all manufacturing industries:

1. The structured processing of benefits revealed that not all benefits, although allocated to separate dimensions with varying scope, are independent from each other. Some benefits are rather mutually dependent and complementary. Thereby, it appears that the implementation of Industry 4.0 technologies to achieve benefits on the operational level is often times a precondition for the realization of benefits on managerial or strategic levels. For instance, the realization of strategic benefits like the alignment of production to changing, individual customer demands requires the realization of production flexibility or an accelerated product development process. Accordingly, the manifold interdependencies inherent in potential benefits must be considered by management, especially in terms of cause-effect relations to determine which benefits are intertwined and to identify all benefits resulting from the implementation of certain enabling technologies.
2. The benefits' assignment to the respective framework dimensions revealed that the line between operational and managerial benefits rather vanishes through the developments of Industry 4.0, especially regarding the production system. Examples for this transformation identified in the framework are benefits concerning adaptability, utilization, optimization, predictive maintenance, or autonomous problem handling. These result from the capability of production systems to provide real-time information on an unprecedented fine-granular level and, thus, to self-control the production process in real-time, a key-characteristic of Industry 4.0. This ability influences traditional planning processes and contributes to an amalgamation of operational and managerial tasks. Thus, management faces the challenge to adapt its managerial processes, accordingly.

3. While some benefits are commonly mentioned to describe the concept of Industry 4.0 (Neugebauer et al. 2016), they are often times not set in context with concrete enabling technologies. Thus, guidance on how to realize specific benefits by means of enabling technologies is missing. This was also found by Strozzi et al. (2017), who state that research focuses primarily on conceptual work and experiments and rarely discusses actual test-beds and lessons learned from practice. Accordingly, management faces the challenge to determine concrete investment measures in enabling technologies and to develop robust transformation roadmaps in the course of their digitalization strategy.
4. Yet, some articles mention first examples for implemented benefits and their enabling technologies. For instance, Herterich et al. (2015) conduct case-studies regarding impacts of CPS on industrial services. Their benefits can be assigned primarily to operational benefits including a reduction of downtime or an increased fix time and rate. This leads to the impression that operational benefits might appear earlier, whereas strategic benefits might materialize on a longer time horizon. A survey conducted by the American Society for Quality mentioned by Banham (2015) gives a similar impression. It reveals that 82% of manufacturers could realize production efficiency gains and 49% could reduce product defects by investing in smart machines. Also, 45% could increase customer satisfaction, which constitutes a strategic benefit. Therefore, management needs to critically review the impacts of employed technologies and establish measures to assess benefits on a longer time-horizon. To evaluate the success of ex-ante pursued benefits, performance indicators should be developed enabling the ex-post evaluation of benefits and their realization. For this, our benefits framework can serve as a starting point.
5. The magnitude and diversity of benefits revealed by our analysis and the accompanying costs and risks of investments clearly indicate the importance for management to systematically evaluate Industry 4.0 technologies and to apply structured approaches to manage benefits actively (Peppard et al. 2015). Accordingly, the comprehensive evaluation of Industry 4.0 technologies requires appropriate qualitative and quantitative methods of economic investment and decision theory. Our structured overview of possible benefits can serve as a starting point, for instance, for a structured benefits management approach by means of a benefits dependency network as presented by Peppard et al. (2015).

IV.1.6 Conclusion, Limitations, and Outlook

The developments of Industry 4.0 lead to the advancing digitalization of production facilities and the development of digital enhanced business models promising great potentials in all manufacturing sectors. The accompanying changes are anticipated to transform business strategies and success models posing a fierce pressure on companies to deal with these developments in a proactive manner. Despite the obvious importance, there was no comprehensive picture of the contribution of Industry 4.0 technologies to the value creation of companies as a structured overview over the benefits of Industry 4.0 was missing. However, this is necessary for a comprehensive identification and subsequent quantification of benefits in regard to value-based investment decision strategies. Therefore, our work contributes to research by developing a structured benefits overview. For this, we identified 365 benefits anticipated in literature, consolidated them to 24 conclusive benefits and categorized them into an IS benefits framework. Our overview demonstrates the different dimensions in which Industry 4.0 technologies contribute to value creation. It becomes apparent that their strategic value resides in optimizing internal and cross-company value creation processes and the opportunity to develop new products and business models.

Despite the merits of this paper in terms of systematically structuring the benefits of Industry 4.0, there are some limitations, which can be noted as potential areas for further research. For instance, our analysis only includes benefits that are mentioned in scientific literature. Therefore, potential benefits that are not considered by researchers, or cannot be conceived yet, are missing. Moreover, this neglects potential findings only included in non-scientific publications. Further, in our literature analysis, we did not consider whether benefits are the focus of an article or only listed for motivational or descriptive purposes. Thus, research building up on our framework has to consider that the feasibility of the latter might not be thoroughly researched yet. Additionally, anticipated benefits in literature address different hierarchical levels (e.g. reduction of waste vs. increase of competitiveness) and are in some cases mutually dependent regarding their realization. This represents a starting point for further research on the hierarchy of benefits, on cause-effect-chains, and on causal relations among complementary benefits that could be displayed by benefit dependency networks (Ward and Daniel 2006). Additionally, we categorize the identified benefits in an adapted IS benefits framework. Future research should examine whether there are other ways of benefits categorization that would also be promising and possibly even more appropriate. So far, there is no empirical evidence in literature and, at the same time, great uncertainty in practice about which of the anticipated benefits might truly become reality. We refrained from theoretically operationalize the respective benefits as the concrete extent and value of a benefit is highly use-case specific and would have exceeded the scope of this paper. Thus, the evaluation and quantification of benefits under consideration of risk and return aspects is another important topic for further research. The same holds true for the development of concrete transformation roadmaps and digitalization strategies that support companies in deriving an appropriate portfolio and sequence of Industry 4.0 projects.

Despite these limitations and open topics for further research, we strongly believe that the developed benefits framework contributes to research on Industry 4.0 and presents a first step in enabling decision makers to identify relevant fields of actions, to develop comprehensive business strategies, and consequently, to derive value from the realization of Industry 4.0 investments.

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IV.2 Research Paper 6: "Creating Competitive Advantage in E-Business Value Chains by Using Excess Capacity via IT-enabled Marketplaces"

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Abstract: *Innovations through the "business process as a service" (BPaaS) concept have shaped new business opportunities for service providers. Technological progress allows business process service providers (BPSPs) to offer a wide range of digitized and standardized services to business clients. Within this business model, capacity planning is a major challenge for BPSPs, as costs are the decisive factor in the competitive business environment of digital service provision. Accordingly, BPSPs must tackle inefficiencies in capacity planning resulting from both idle capacity and lost revenue caused by volatile demand. However, recent technological developments offering dynamic integration and information capabilities may help, as they enable the exchange of excess capacity between business partners. We examine the corresponding potential of IT-enabled excess capacity markets to create competitive advantage in e-business value chains by analyzing a BPSP's capacity-related optimization problem. We build an analytical model based on queuing theory and evaluate it through a discrete-event simulation applying a possible application scenario. By solving the optimization problem, we identified a remarkable cost advantage in using excess capacity as a first competitive advantage. Building on this cost advantage, we*

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[1] The affiliation of Jochen Übelhör has been updated because he changed his job after the acceptance of the paper.

furthermore identified differentiation advantages realizable without raising prices. Both findings highlight the relevance of further research on this topic.

IV.2.1 Introduction

The increasing digitization of business processes, along with modern information technology (IT), allowing a fast and easy integration of business partners leads to a continuing and radical transformation of e-business value chains as well as new and innovative forms of cooperation (Barua, Konana, Whinston & Yin, 2001; Andal-Ancion, Cartwright & Yip, 2003; Ramirez, Melville & Lawler, 2010). Companies can now source whole business processes from external providers that allocate all technical, personnel, and other resources necessary to ensure an effective and efficient process operation (Sengupta, Heiser & Cook, 2006). Especially for standardized, IT-driven, and digitized business processes, the well-known business process outsourcing (BPO) approach has already evolved, leading to the “business process as a service” (BPaaS) concept. By analogy with concepts such as software or infrastructure as a service, BPaaS describes a dynamic BPO relationship between a business process service provider (BPSP) and its business clients: Both parties technically integrate their processes via Internet-based technologies, allowing the BPSP to deliver its service within a flexible contract period and a consumption-based pricing model. Moreover, the BPSP can share its resources among different business clients flexibly in order to ensure service provision as stipulated in the applicable service level agreement (SLA) (PricewaterhouseCoopers [Pwc], 2010).

As companies usually keep core business processes in-house (e.g., to avoid drain of critical business knowledge), BPSPs mostly offer standardized support for business tasks that do not demand specialized competencies. The range of business processes currently available as services include online payment processing, human resources and procurement services, and other back-office tasks (Pwc, 2010; Kaganer, Carmel, Hirschheim & Olsen, 2013). For instance, in the banking industry, automated bank account relocation services are provided by BPSPs. These services are usually commodities with few distinguishing characteristics and can be offered by a wide range of BPSPs. Especially for such commodity services, business clients aim to minimize the costs of service purchasing; thus, service price is the decisive competition factor among BPSPs (Dorsch, 2013). Further, even highly specialized business processes like automated credit assessment and credit decision-making that require more specialized capabilities and posse a high degree of criticality, e.g. in terms of timing requirements, can also be handled by BPSPs. Accordingly, to succeed in this cost-driven environment, BPSPs must identify and raise potentials for more cost-efficient service provision to realize competitive advantages. To outperform its competitors, a BPSP must either provide the established service level at less than the competitive price or provide improved service at the established price.

An important strategic lever for achieving cost and price leadership is a sophisticated ex-ante planning of the BPSP's in-house capacities. This is especially important due to the characteristics of service provision: most BPSPs face very volatile demand but are not able to react to demand fluctuations by scaling their IT capacity or their personnel resources on short notice. At the same time, business clients usually specify service quality such as fast response times by contracting SLA with penalty payments in case of insufficient service provision (Chesbrough & Spohrer, 2006; Rai & Sambamurthy, 2006). Consequently, to avoid SLA-related penalties, the BPSP must be able to cover peak demand while also ensuring the efficient use of resources to avoid idle costs in times of average or low demand (Bassamboo, Ramandeep & van Mieghem, 2010a; Bassamboo, Ramandeep & van Mieghem, 2010b). Finding the right balance within this tradeoff is a major key to superior resource usage and a foundation for generating competitive advantage in such cost-driven environments.

In addressing this tradeoff, most methods of handling analogous capacity planning problems in manufacturing (e.g., producing on stock to cover peak demand) cannot be applied to BPSP due to specific service characteristics like non-storable services with uncertain demand. However, when focusing on IT-driven and digitized services, the development of innovative technologies such as service-oriented architectures, cloud-computing, and associated concepts may help mitigate this capacity planning problem. As these technological developments strongly foster firms' integration capabilities of third-party providers, they are also the catalyst for *IT-driven marketplaces*, allowing business partners to interact in a highly dynamic manner (Grefen, Ludwig, Dan & Angelov, 2006; Moitra & Ganesh, 2005). At this, an IT-driven marketplace provides an information platform for a coordinated interplay of its market participants that allows matching available excess capacity with excess demand. Consequently, these new possibilities offer a promising opportunity for exchanging excess capacity to address the tradeoff between idle costs and waiting costs. The in-house capacity of the BPSP can be reduced because excessive demand can be routed to third-party providers with underutilized IT and/or personal capacities forming the *excess capacity market* (ECM).

However, using excess capacity bears additional risk. For instance, excess capacity's availability can be limited. Hence, a BPSP has to consider the risk of waiting times at the

ECM when deciding about its in-house capacity and must balance it against the potential economic benefits of an ECM.

This economic potential may be hampered, as not all service requests can or will be routed to the ECM since service requests can differ in terms of specific characteristics such as data quality, legal requirements, or confidentiality (Braunwarth & Ulrich 2010; Braunwarth, Kaiser & Müller, 2010). Thus, when deciding ex-ante about the appropriate level of in-house capacity, the BPSP must consider the inhomogeneity of service requests and, in particular, the expected number of such requests that can or will not be routed externally. Thereby, we define inhomogeneity as the difference of single service request in terms of specific characteristics such as data quality, legal requirements, or confidentiality.

Against the background of a highly competitive market for cost-driven inhomogeneous services, we examine how a BPSP can create competitive advantages through an IT-enabled ECM within its value chain. The central research question of our paper is as follows:

Which competitive advantages can be realized through an IT-enabled ECM within a BPSP's value chain regarding the processing of cost-driven inhomogeneous service requests?

To evaluate the ECM's potential to create competitive advantage, we use a design-science driven research approach and follow its basic paradigm of gaining knowledge by developing and evaluating specific artifacts (Hevner, March, Park & Ram, 2004; Peffers, Tuunanen, Rothenberger & Chatterjee, 2008). With our optimization model we depict the capacity planning problem of a BPSP considering the option of using an ECM and demonstrate the potential of an ECM for creating competitive advantages. We evaluate our model through a discrete event simulation and. Thereby, we identified a remarkable *cost advantage* in using the ECM to process a certain portion of incoming requests in different types of digitized business processes. Building on this *cost advantage,* we examined the possibilities of gaining a *differentiation advantage* and showed that reduced processing times can be guaranteed and executions times (and thus quality) can be increased at equal costs, leading to a competitive advantage. We further discuss the use and strategic advantages of an ECM in different possible digitized business processes by considerably fluctuating model parameters around the values of the initial scenario.

The remainder of this paper is organized as follows: First, we analyze the literature to highlight the research gap this study addresses. Second, we develop the optimization model using queuing theory. We then perform discrete-event simulations in a case study of online identification and authorization services for retailers such as online banking or trading platforms and investigate strategic implications of ECM usage. Finally, we summarize the key findings of the paper and discuss possibilities for future research.

IV.2.2 Related Work

Several streams of literature are considered to carve out the research gap and provide the theoretical foundation for our optimization model. First, we briefly overview the literature concerning IT's general role in gaining competitive advantages. Then, we discuss the literature related to the problem of ex-ante capacity planning for services. Finally, we overview the literature on the use of IT-enabled excess capacity markets for services and their potential for ex-ante capacity planning.

IV.2.2.1 IT and Competitive Advantages

The strategic significance of IT and its relevance for creating competitive advantages has been broadly addressed in the literature. According to Porter and Millar (1985), IT is "transforming the nature of products, processes, companies, industries, and even competition itself." Therefore, IT can affect and reshape business value chains as well as change the structure of whole industries. Furthermore, IT can create competitive advantages by giving companies new ways to outperform their competitors and spawn new businesses from within existing operations (Porter & Millar, 1985). Powell and Dent-Micallef (1997) show that companies have gained competitive advantages by using IT to leverage human and business resources. Various other studies, such as Peteraf (1993), Grant (1991), and Barney (1991), follow this resource-based view and emphasize that a company`s ability to generate competitive advantages is directly determined by its superior usage of resources and capabilities. Furthermore, numerous empirical studies confirm the strong relationship between a company's IT capabilities and firm performance (e.g., Bharadwaj (2000), Santhanam and Hartono (2003), Aral and Weill (2007), Rai, Patnayakuni and Seth (2006), Stoel and Muhanna (2009), or Ravichandran, Lertwongsatien and Lertwongsatien (2005)).

For BPSPs operating in a cost-driven market and following the basic principles of Porter and Millar (1985), there are two possible business strategies. It can offer the established service at less than the competitive price or it can offer an improved service (e.g., through an improved SLA) at the established (competitive) price. Differentiation strategies such as offering a significantly improved service for a *higher* price are barely relevant for the provision of very standardized services, as price is the decisive factor. The relevant differentiation strategies for BPSP in such a cost-driven market must therefore build directly on cost advantages. A BPSP will obtain these cost advantages mainly through superior usage of resources (i.e., by providing cost-efficient services). Thus, the usage of an IT-enabled ECM might offer the potential to reduce fixed costs for maintaining internal capacities, generating a competitive cost advantage. According to Mata, Fuerst and Barney (1995), this competitive advantage can be either sustained or temporary depending on the level of challenges competing firms face when trying to imitate and reproduce the strategy. The competitive advantage created through the usage of IT-enabled ECM is therefore not expected to be fully sustainable, since it decreases over time as an increasing number of competitors acquire the competencies and resources (e.g., IT capabilities and skilled personnel) necessary to duplicate the strategy. Nevertheless, companies can create at least a temporary competitive advantage by implementing ECM usage before most of their direct competitors do. As a functioning ECM requires a minimum number of participants, it is important to understand that, due to the high degree of service standardization, both competitors as well as non-competing companies can participate in the ECM. This supports the possibility of using excess capacity to realize at least a temporary competitive advantage, as the participation of direct competitors in the ECM is not a prerequisite for its emergence.

IV.2.2.2 Outsourcing and Capacity Planning for Service Provision

Outsourcing and corresponding effects on capacity planning have been well researched in literature. For instance, Kremic, Tukel and Rom (2006) conclude based on an extensive literature review that strategic motivations for outsourcing can be categorized as follows: cost, strategy, and politics (mostly for public organizations). In literature, mainly transaction-cost-theory is applied to investigate cost saving potentials due to specialization and economies of scale, while resource-based view is applied to explain outsourcing from a strategic perspective (Boulaksil & Fransoo, 2010). Thereby, companies outsource tasks to concentrate on core competencies or to increase flexibility for managing uncertain demand (Lankford & Parsa, 1999). Regarding the outsourced tasks, two types can be differentiated: the outsourcing of storable goods and the outsourcing of non-storable goods and services. Both are well researched in literature. For example, Dong and Durbin (2005) investigate surplus production markets that enable the exchange of excess components between suppliers with excess inventory and manufacturers with shortage. They show that participants can profit from the exchange of excess inventory on surplus markets.

The general problem of ex-ante capacity planning for non-storable goods and services under uncertain demand has also long been examined in scientific literature. In particular, the topic of call center outsourcing, which reflects a common example for capacity planning for services, has been widely discussed. These studies usually distinguish between the two basic sourcing models that companies can use: volume-based contracts and capacity-based contracts (Milner & Kouvelis, 2007; Ghose, Telang & Krishnan, 2005). Volume-based contracts ("pay-for-job") involve payments only for the used capacity, whereas capacity-based contracts ("pay-for-capacity") involve payments for all capacity, whether employed or not. Considering these basic sourcing models, Akşin, de Véricourt and Karaesmen (2008) determine the optimal capacity levels and partially characterize the optimal pricing conditions for each type of contract. Gans and Zhou (2007) analyze the centralized capacity and queuing control problem within this context. Studies dealing with outsourcing decisions in a service setting include Ruth, Brush and Ryu (2015), Cachon and Harker (2002), Allon and Federgruen (2008), and Ren and Zhou (2008). Ruth et al. (2015) investigate by means of transaction-cost and agency-cost the influence of IT on outsourcing decisions and the level of centralization of HR-related services within a firm. Based on a survey among 243 firms, they find that IT facilitates outsourcing. Cachon and Harker (2002) study the competition between two service providers with price- and time-sensitive demand by modeling this setting as a queuing game. Allon and Federgruen (2008) analyze volume-based contracts and their effects on supply chain coordination. Ren and Zhou (2008) study contracting issues between a client and a vendor and analyze contracts the client can use to induce the vendor to choose staffing and effort levels that are optimal for the supply chain. The aforementioned studies analyze various aspects of volume- and capacity-based contracts in the context of capacity planning for services, but they do not consider the option of IT-enabled exchanges of excess capacities. However, an understanding of the influence of IT-enabled exchanges of excess capacities on ex-ante capacity planning decisions is highly important, as IT-enabled ECMs, in contrast to conventional exchange markets, enable the highly dynamic and automated exchange of excess capacities between business partners and influence the operational principals of such excess capacity markets (and thus their advantageousness).

IV.2.2.3 IT-enabled Markets for Excess Capacity

This paper focuses on how IT-enabled ECMs foster the exchange of excess capacities between companies and thus addresses the problem of ex-ante capacity planning for BPSPs. The basic idea of exchanging capacities to facilitate ex-ante planning has been discussed in production and supply chain management studies on the so-called "surplus markets" (Gans & Zhou, 2007; Akşin et al. 2008; Cachon & Harker, 2002; Allon & Federgruen, 2008; Ren & Zhou, 2008). These papers are related to our approach, as firms with a shortage of capacity or inventory can buy available overcapacities or excess inventories from other firms. In a fundamental difference, however, these papers deal with physical products and examine the trading of physical excess inventories.

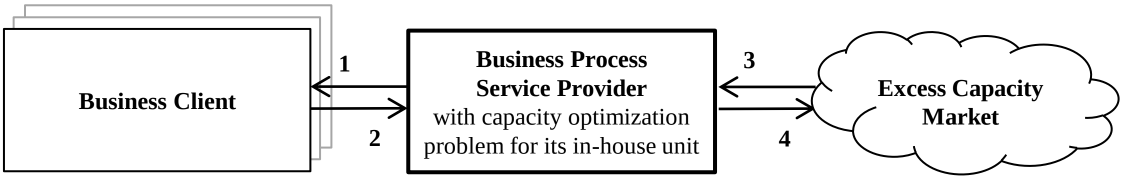

Figure IV.2-1 The business process service provider's value chain

By contrast, we seek to facilitate capacity planning for digital, non-storable IT services with uncertain demand by using IT-enabled ECM (cf. Figure IV.2-1). The usage of IT-enabled ECM and the potential for the ex-ante capacity planning for digital services has been examined only recently by Dorsch and Häckel (2012a, 2012b, 2014). Dorsch and Häckel examine the cost advantage to service providers of the on-demand integration of business partners (Dorsch & Häckel, 2012a) and analyze the environmental sustainability benefits of excess capacity markets in cloud service environments (Dorsch & Häckel, 2012b). The advantages of combining the usage of on-demand surplus capacity with classical models of capacity supply (dedicated capacity and elastic capacity) are also elaborated (Dorsch & Häckel, 2014). Though this research provides valuable insights into the impact of an IT-enabled ECM on capacity planning for services, it focuses on the realization of cost advantages in processing homogeneous services. Our approach differs in two key ways. First, we explicitly consider the given inhomogeneity of service requests (Braunwarth & Ulrich, 2010; Braunwarth et al., 2010) by acknowledging that not all requests can or will be processed on external markets. Second, we investigate how a BPSP can gain differentiation advantages through an IT-enabled ECM, comparable to the concept of reinsurance in the insurance industry. We therefore extend the existing models significantly and examine how competitive advantages can be generated in this distinctly more complex and realistic scenario.

In the following, we present a modeling approach to help optimizing the ex-ante capacity planning of a BPSP when considering the option of using an IT-enabled ECM. Within this modeling approach, we consider the inhomogeneity of service requests. The results of this optimization model provide valuable findings on the possible competitive advantages enabled by IT-enabled ECM.

IV.2.3 Modeling the Business Process Service Provider's Value Chain

To substantiate the idea of IT-enabled ECM and demonstrate our model, we first elaborate on our research methodology, then describe the general setting and discuss the necessary information and integration capabilities. Then, we define the model and its assumptions, starting with the underlying capacity optimization problem, followed by a description of the in-house unit and the ECM and all relevant parameters and (objective) functions. Finally, we introduce a routing algorithm necessary to solve the optimization problem.

IV.2.3.1 Research Methodology

To address the raised research question, we apply a typical design-science driven research (DSR) approach (Hevner et al., 2004, Peffers et al., 2008). DSR in information systems (IS) is important to solve organizational problems and gain knowledge of a problem by the development of artifacts (Hevner et al., 2004, Peffers et al., 2008). The typical DSR methodology (Peffers et al., 2008) suggests six activities: (1) identify problem; (2) define design objectives for solution; (3) design and develop; (4) demonstrate; (5) evaluate; and (6) communicate. The first activity was already addressed by highlighting the relevance of formalized methods for the depiction and simulation of ECM’s potential to create competitive advantage in the introduction Section. In the following, we start with the development of an artifact, an optimization model depicting the capacity planning problem of a BPSP considering the option of using an ECM, as building a mathematical model is one common way to represent an artifact in a structured and formalized way (Hevner et al., 2004). Next, we describe a detailed real world scenario (descriptive design evaluation method) and evaluate our model through a discrete event simulation, a widely accepted experimental design evaluation method (Wacker, 1998). To ensure utility as a major goal of design-science research (Hevner et al., 2004), we aim to demonstrate how our approach can be applied to a specific scenario and how the advantages of using an IT-enabled ECM can be valuated based on this model. Our approach is also closely related to the research cycle of Meredith, Raturi, Amoako-Gyampah and Kaplan (1989) who emphasize that describing non-examined research areas qualitatively and mathematically and thus predicting first results provides the basis for generating hypothesis that can be tested within future empirical research. To outline directions for further research, we discuss next steps regarding our optimization approach that might be addressed by applying various empirical evaluation methods like e. g. case studies, field studies or field experiments at the end of the paper.

IV.2.3.2 General Setting and Necessary Information and Integration Capabilities

We consider a three-stage e-business value chain, as illustrated in Figure IV.2-1. Here, a BPSP offers an IT-driven service to numerous business clients. The activities necessary to provide the service require IT as well as personnel resources because some activities require manual interventions. As the execution of the service is time-critical, the BPSP offers an SLA to its business clients (arrow number 1). The business client's requests are characterized by volatile demand (arrow number 2). As neither the IT capacity nor the personnel resources are fully scalable on short notice, the BPSP faces a capacity optimization problem for its in-house unit: to avoid both costly violations of the committed SLA due to capacity shortages in times of peak demand and idle costs in times of low demand, internal resources must be properly balanced. In addition, the BPSP can use the ECM to route certain service requests to third-party providers, offering their temporarily unused capacity (arrows number 3 and 4).

Though service requests have standardized purposes, they are inhomogeneous in terms of the requirements of individual requests. Thus, following recent studies on (IT) business process outsourcing (e.g., McIvor (2008) or Atkinson, Bayazit and Karpak (2015)), the BPSP divides incoming requests into two categories: requests that can be routed to the ECM (the *regular requests*) and those that need to be processed by the in-house unit of the BPSP (the *special requests*). Special requests may require specific expertise only available at the BPSP's in-house unit, or they must be processed in-house due to legal or confidentiality requirements. Therefore, the BPSP has to consider these two categories when optimizing the BPSP's in-house capacity. As a consequence, the competitive advantages that can be achieved through an ECM as well as the appropriate level of in-house capacity are highly dependent on the inhomogeneity of incoming service requests. Furthermore, as excess capacity can be booked only on short notice, it is usually not SLA-backed, and its use tends to be more risky (due to possible delays) but also cheaper than in-house processing (as there are no idle costs). Thus, to decide whether an external execution of regular requests is preferable, the BPSP has to compare the costs for external execution and the risk of possible delays against the total processing costs of the in-house unit.

To operationalize the use of excess capacity, the BPSP must develop several *integration and information capabilities*. Building these capabilities is an essential precondition of realizing competitive advantages through excess capacity. In concrete terms, the BPSP must be able to (1) automatically determine which of the third-party providers is offering excess capacity on the market at any point during operation, (2) gather all the information relevant to its decision (e.g., current waiting time until external capacity is available, price for processing the request), and (3) connect its IT system to that of the third-party provider. Thus, its own IT system has to allow for a continuous evaluation of the ECM, and all necessary information must be provided by the ECM. The supply of information is supported by high-level frameworks for information exchange such as BizTalk, ebXML and RosettaNet as well as by various B2B platforms offered by product vendors (e.g., Oracle, Microsoft, IBM). In recent years, the web service paradigm emerging with service repositories and well-described services based on standardized description languages have evolved into one of the primary standards for the dynamic evaluation and integration of service providers (Grefen et al., 2006). Through these technological developments, a decentralized information exchange between various service providers regarding the usage of excess capacity is possible. Furthermore, a more centralized approach has been enabled by the development of (on-demand) service marketplaces such as SAP Service Marketplace, HubSpot, or Zimory, by which firms offering or/and seeking certain services can interact in a highly dynamic manner (Grefen et al., 2006; Weinhardt et al., 2009).

IV.2.3.3 Underlying Capacity Optimization Problem

As mentioned, each incoming request triggers a service execution. The arrival rate λ (i.e., the number of time-critical requests sent from the business clients per time unit) is random. The statistical distribution of λ can be approximated based on historical data. The planning horizon considered is finite and divided into equidistant time units. After the BPSP has finished all activities necessary to complete the request, it is returned to the respective business client. The time frame between the accepting and returning of the request is called the *processing time*. Service level s (e.g., a maximum processing time with penalty payments for each time unit the request exceeds this limit) is guaranteed to the business clients for this processing time. Any request that fails to maintain this service level causes costs subsumed within c_s.

Taking these characteristics into account, the BPSP must decide ex-ante on the capacity (i.e., the number of requests $y \in IN_0$ that can be handled simultaneously) to allocate to its in-house unit, which minimizes its *total processing costs* c. The simplified objective function for this discrete optimization problem is therefore given by

$$\min_{y} c(\lambda, y, s)$$

Concerning these main characteristics (e.g., random demand, limited capacity), it is appropriate to model the capacity optimization problem using *queuing theory*. In the following, we therefore rely on its basic assumptions as described, for example, in Gross, Shortle, Thompson and Harris (2008), while extending them by the necessary parameters and functions.

IV.2.3.4 Service System of In-house Unit and Excess Capacity Market

Unless all capacity units within the in-house unit are busy, the execution of a request starts immediately after its arrival in the BPSP's IT system. If all units of capacity are busy, each incoming request lines up in an infinite waiting queue, to be executed immediately when capacity is available again, i.e. as soon as a request has been processed. Free units of capacity are idle and cannot be used to accelerate the execution of other requests. The timeframe within which the request stays in the queue in front of the in-house unit is called *waiting time*. The timeframe between the beginning of the service's first activity and the end of the last is called *execution time*. Accordingly, waiting and execution time sum up to the *processing time* mentioned above. Hence, long waiting times might lead to processing times that do not maintain the agreed service level and cause corresponding costs.

In addition to the in-house unit, third-party providers offer excess capacity for temporary use, forming an ECM. On this market, capacity cannot be booked in advance, and constant availability is not enforced by SLA. The availability of capacity on the ECM therefore changes constantly, and a non-negligible and risky waiting time must be considered when relying on the ECM. This exogenous waiting time for capacity on the ECM has to be provided constantly by third-party providers. Timeframe a denotes the time a request must wait in the ECM queue. With $a > 0$, requests cannot be executed immediately, and the exogenous waiting time might be too long to keep up with the service level agreed with the business clients, causing corresponding costs.

When considering the ECM as a second queuing system, the combination of in-house capacity and ECM forms a *service system* that offers two separate *execution paths* for incoming service requests. Thus, as illustrated in Figure IV.2-2, the BPSP can decide whether it routes a (regular) request to the in-house unit or to the ECM. As mentioned, special requests can be executed only in-house due to reasons of competence, confidentiality, or legality.

IV.2.3.5 Total Processing Costs and Detailed Objective Function

To determine the actual total processing costs c, additional parameters specifying the two queuing systems are necessary and the *execution time* for regular and special requests must be determined: Considering a special request, the statistical distribution of the execution time t_s within the in-house unit can be derived based on historical data. Likewise, the statistical distribution of the execution time t_r for a regular request can be determined. The *in-house unit* causes *fixed costs* c_f per unit capacity but no additional *variable costs*. The fixed costs considered for one unit of capacity contain recurring capacity costs such as employee wages, running costs for the IT system and other equipment, overhead costs, and all non-recurring initial costs. The total number of regular requests finally processed in-house is denoted by $o_{i,r}$, and the total number of special requests executed in-house is denoted by $o_{i,s}$. The *external execution* involves no fixed costs, but variable costs c_e for each request sent to the ECM. As prices may change during operations, price c_e must be provided along with the information about the waiting time a, as described above. The total number of externally routed regular requests is denoted by o_e.

We can now determine the BPSP's total processing costs. The detailed objective function reads

$$\min_{y} c = c_f\, y + c_e\, o_e + c_s\big(\lambda, y, o_{i,r}, o_{i,s}, o_e, s, t_r, t_s, a\big)$$

As mentioned, the total processing costs considered in this model consist of the fixed costs c_f of in-house capacity, the variable costs c_e of using excess capacity, and the costs c_s resulting from requests that violated the SLA (i.e., *compensations* for delayed requests and *penalties* for requests that remain unexecuted). Consequently, the optimization problem is related to the amount of capacity y the BPSP allocates to the in-house unit. Integrating the ECM changes the total processing costs c, as the processing costs of regular requests differ depending on the execution path and overall waiting times. Solving the objective function for the integer values of y results in the optimal amount of capacity the BPSP should allocate in-house to minimize total operating costs. Figure IV.2-2 and Table IV.2-1 summarizes the model (parameters).

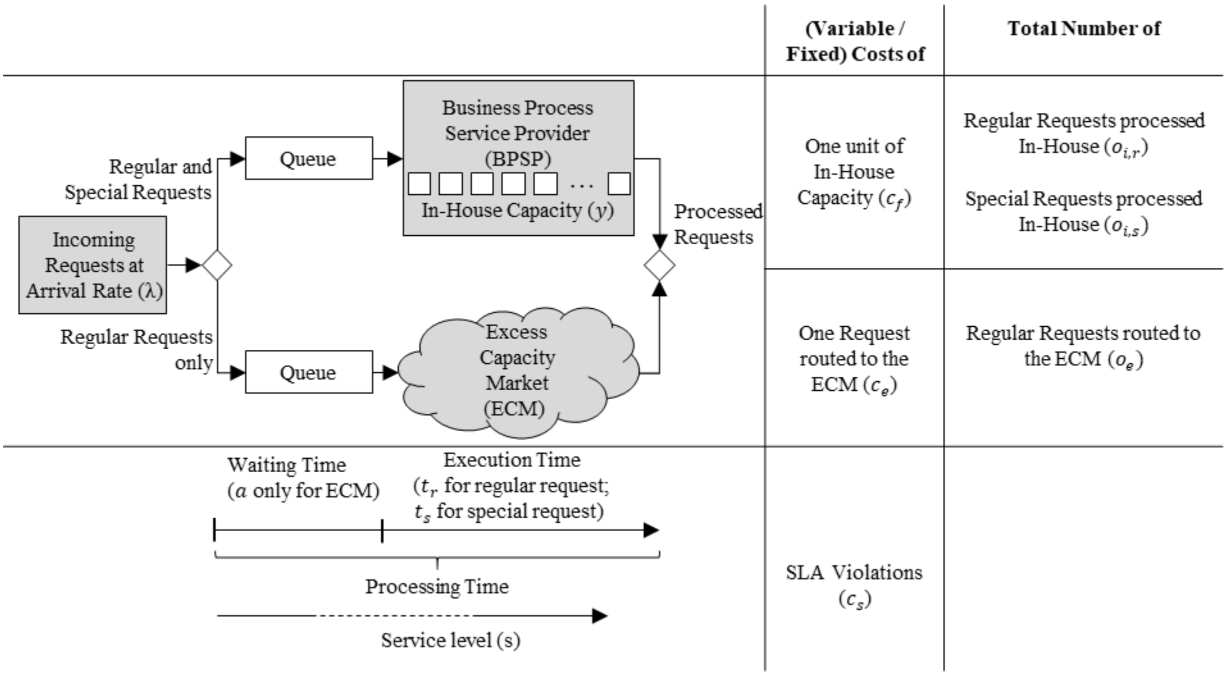

Figure IV.2-2 Service system with two queuing systems

Category	Notation	Description
Costs	c	Total processing costs
	c_f	Fixed costs of one unit of in-house capacity
	c_e	Variable costs of one request routed to the ECM
	c_s	Costs resulting from requests that violated the SLA (i.e., *compensations* for delayed requests and *penalties* for requests that remain unexecuted).
Requests	$o_{i,r}$	Total number of regular requests processed in-house
	$o_{i,s}$	Total number of special requests processed in-house
	o_e	Total number of regular requests routed to the ECM
Execution Time	t_s	Execution time for a special request.
	t_r	Execution time for a regular request
Other	y	Units of in-house capacity (optimization variable)
	λ	Arrival rate, i.e. the number of time-critical requests sent from the business clients per time unit
	a	Waiting time in queue for a request routed to the ECM
	s	Service level, i.e. a maximum processing time with penalty payments for each time unit the request exceeds this limit

Table IV.2-1 Notation overview

IV.2.3.6 Routing Algorithm Necessary to Solve the Optimization Problem

To solve this optimization problem, it is not sufficient to evaluate the two queuing systems representing the in-house unit and the ECM separately. Rather, the service system must be evaluated as a whole because the two queuing systems interact during operations and influence waiting times. Although queuing theory provides a strong mathematical foundation, this cannot be done analytically since the two queuing systems have different characteristics, especially concerning their distribution of processing times.

The routing decision must take place during operations for every single request immediately after arrival. In the beginning, the IT system must separate regular requests from special ones. Then, the routing decision requires a routing algorithm that links the two interacting queuing systems and decides about the execution path for a regular request.

The routing algorithm works as follows (cf. Figure IV.2-3). First, it determines the processing time for each queuing system. This is easily determined for the in-house unit, as the state of the system depends on its own capacity y, the arrival rate of requests λ, and the execution time t_r. Besides, the timeframe a until free capacity is available on the ECM has to be determined. Second, if these processing times result in a violation of agreed-upon service level s, SLA-induced compensations and penalties must be calculated. The tradeoff between additional variable external execution costs c_e and a possible reduction of compensations and penalties c_s builds the basis for this decision. Third, having determined processing times and considered the SLA effects, the processing costs of each execution path for each request, and thus the preferable path for the execution, can be determined.

To demonstrate our model, we present an application scenario based on a real-world example. We perform a discrete-event simulation, an established method for analyzing queuing systems (Gross et al., 2009). Our simulation implements the quantitative optimization model described above with all relevant cost functions and parameters of the described tradeoff. Furthermore, the necessary routing algorithm is implemented to evaluate the interaction of both queuing systems. Through this method, a simulation-based optimum ("optimal capacity" hereafter) can be determined for different scenarios in order to answer our research question.

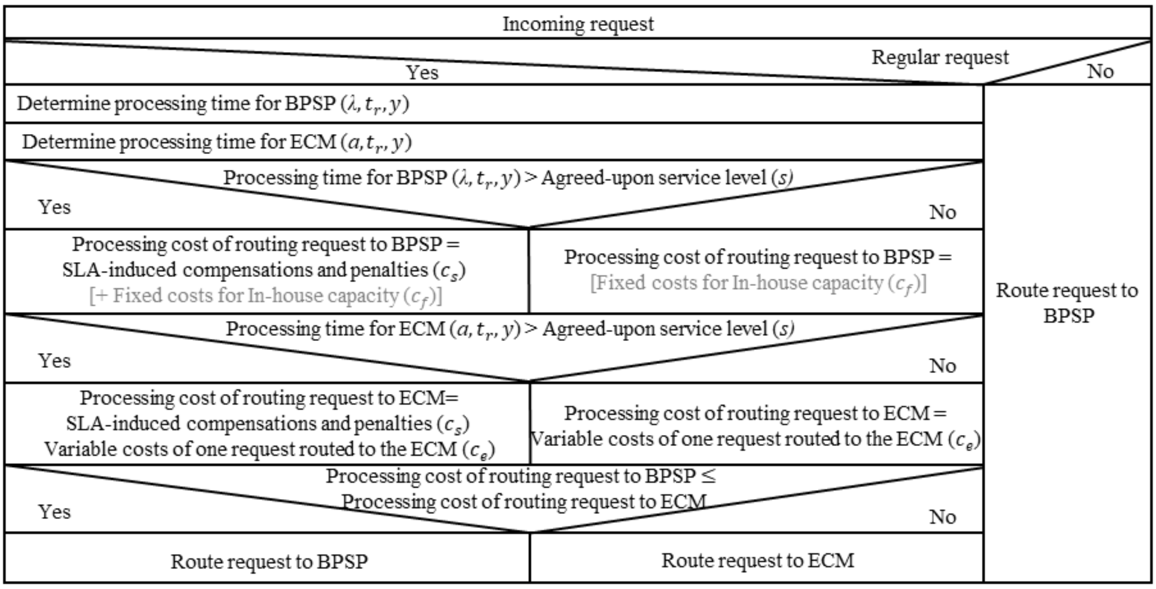

Figure IV.2-3 Routing Algorithm

IV.2.4 Evaluating the Potential of Excess Capacity Markets

To evaluate the potential of integrating excess capacity to create competitive advantages and to demonstrate the feasibility of our model, we conduct simulations for a real-world example in an artificial setting enabling different scenario analysis. The application of simulations is reasonable as different input parameters influence the cost advantageousness of ECMs and, at the same time, make it difficult for human decision-makers to weigh corresponding decisions under consideration of all influencing factors. For this, in our simulation, we present the application scenario of a specific BPSP, a payment service provider (PSP) offering online identification and authorization services and electronic payment processing (e.g., Amazon Payments, PayPal). These services are typical tasks required by online retailers such as stores, trading platforms, and financial institutions. Of course, specific BPSP settings in reality are far more complex including a variety influencing factors. Nevertheless, the simulation of a close-to-real-world scenario within our simulation and its results demonstrate that our model is principally suitable for more complex scenarios and provides a basis for the profound economic evaluation.

In the following, we first define the process subject to our exemplary application and describe the related capacity planning problem of the PSP. Next, we determine the input data of our application scenario that are necessary to parameterize our model. The parameterization of the input data is based on various expert interviews as well as many years of experience from prior research in applied research projects with companies in corresponding industries. We then describe the simulation approach to determine the optimal in-house capacity for the process. Finally, we analyze the resulting cost advantage of excess capacity as well as possible differentiation opportunities to investigate strategic implications of excess capacity markets.

IV.2.4.1 Characteristics of the Authorization Process

The digitized business process considered is the identification and authorization process for new customers of online retailers, as illustrated in Figure IV.2-4. This task is usually sourced as a service from specialized PSPs linked with the corresponding institutions (e.g., credit card-issuing banks, credit rating agencies, government offices) necessary to identify (e.g., check and verify personal data, address data, and credit card information) and authorize (e.g., after a credit assessment) a customer. The customer data required for the request are forwarded by the retailer to the PSP for processing.

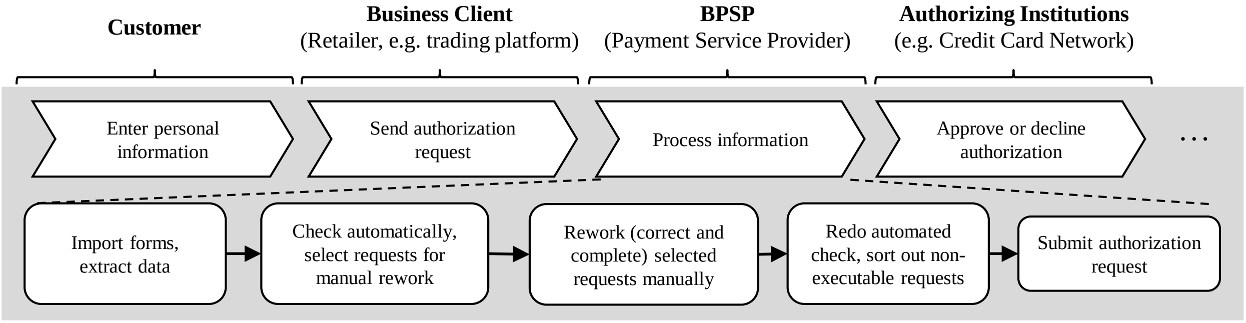

Figure IV.2-4 Simplified identification and authorization process

Though this service is mostly digitized and highly standardized through common interfaces and standard input forms, it requires both intensive IT-supported and manual interventions, such as for reviewing customer inputs (due to reasons of data quality and validity) and identifying erroneous entries. As the correctness of all entered data is essential, the PSP must perform adjustment processes such as (auto)correction, or, if necessary, it must contact the customer for further inquiries. Due to the possibility of customer or third-party interactions, the authorization process must occur during business hours.

The online identification and authorization service is a typical application scenario addressed by our model, as many requests characterized by volatile demand must be processed in time to avoid penalties or loss of customer interest. Therefore, detailed service levels concerning the timeframe for execution are agreed between the retailer and the PSP. Allocating IT capacity and employees to the in-house unit charged with processing the registration procedures is an important optimization problem for the PSP. As the margins are small, the in-house unit's capacity should be kept as small as possible to keep the corresponding costs to a minimum. Along with the volatile arrival rates of incoming requests, there is a tradeoff between idle times and delayed execution.

An ECM can be used through the technologies and standards described above; requests submitted into the provider's gateway are not executed by its respective in-house unit but with the ECM capacity. However, only procedures that do not require adjustments of input data or customer callbacks can be routed to the external market due to reasons of expertise and reliability. Accordingly, the PSP has to decide for each incoming request if the external execution path is suitable (i.e., regular requests) and then if routing the request to an external provider would reduce overall processing costs.

IV.2.4.2 Input Data of the Authorization Process

We determine the input data characterizing the authorization process for our simulation. Authorization requests can be processed each day between 8 a.m. and 6 p.m. Requests that arrive outside these hours are still accepted, but authorization will be executed on the following day. Analyzing the historical data reveals different peaks for incoming request arrival depending on exogenous factors such as customer behavior and demand. Dividing the ten hours of processing time in six timeframes, the arrival rate within each timeframe can be approximated by a negative exponential distribution with different means (per minute), as summarized in Table IV.2-2.

We assume that 30% of all authorization requests require specialized interventions or callbacks with customers due to incomplete or incorrect application forms. Accordingly, these *special requests* have to be executed in-house, notwithstanding the existence of an ECM. The interventions performed on a regular or special request require one unit of capacity for about 12:00 minutes on average regardless of its execution path. As only one employee can work on one request, idle capacity cannot be used to accelerate the execution of other requests. Cost accounting reveals that one unit of capacity within the in-house unit causes fixed costs of $350 per day.

In e-business, requests must be executed in time to meet external deadlines and avoid loss of customer interest. Furthermore, especially for the sake of reputation, satisfaction, and the retailer's economic interests, no request must be left unexecuted. Therefore, the SLA between the retailer and the PSP consists of two deadlines. First, each request has to be processed within 26:00 minutes after arrival. If a request exceeds this timeframe, a compensation that increases with the duration of the time exceeding this deadline is due. The agreed-upon compensation is determined by $\$0.03 * (minutes\ exceeded)^{1.5}$. Second, there is a final processing deadline for each day: All incoming requests have to be processed until 8:00 p.m. For each request not processed within this deadline, the compensation payment is increased by a penalty of $300. Through this penalty, the retailer offers a strong incentive to execute all incoming requests within a day. Compared with the revenues earned by processing a request, the penalty for the final processing deadline is prohibitive.

For simplicity, the variable costs for one request routed to the ECM are fixed at $8 in the simulation. The waiting time for excess capacity can be approximated based on historical data provided by the external service providers. For one day, three timeframes with different availabilities of the external service provider's capacities are identified. Each timeframe shows different waiting times for free capacity, which can be approximated by a normal distribution, as outlined in Table IV.2-3. Requests routed to the ECM have to wait according to the timeframe valid at the time the request is routed to the ECM. With these characteristics, the discrete event simulation now can be established.

Timeframe	Mean [min]
08:00 a.m.–09:30 a.m.	50
09:30 a.m.–11:30 a.m.	3
11:30 a.m.–12:00 noon	30
12:00 noon–01:30 p.m.	5
01:30 p.m.–04:00 p.m.	10
04:00 p.m.–06:00 p.m.	40

Table IV.2-2 Incoming requests

Timeframe	Distribution [min]
08:00 a.m.–12:00 noon	μ = 16:40; σ = 4:00
12:00 noon–02:00 p.m.	μ = 12:00; σ = 2:10
02:00 p.m.–06:00 p.m.	μ = 10:00; σ = 4:00

Table IV.2-3 External waiting times

IV.2.4.3 Discrete Event Simulation

To determine the optimal capacity allocated to the in-house unit, we apply the following procedure within the simulation software used to implement the model. We perform multiple *simulation experiments* with increasing integer values for the capacity of the in-house unit. Each experiment consists of 800 *simulation runs*. The total processing costs are determined for each run. Starting the experiments with one unit of in-house capacity, we increase the value by one unit before the next experiment begins. This is done until the results of an experiment show that no waiting costs occur in front of the in-house unit for all runs. Consequently, an increase in capacity has no positive effect on the total processing costs. Finally, comparing the average total processing costs for each experiment and choosing the one with the lowest costs produces the optimal in-house capacity.

Regarding the simulation time, it is convenient that all days of our application scenario are independent of each other (e.g., with no unexecuted requests left due to the processing deadline at 8:00 p.m.), and the relevant events determining the optimal in-house capacity are recurrent each day. It is thus sufficient to simulate a single day to determine the optimal capacity.

For each simulation run, incoming requests are generated randomly following their statistical distributions. Whenever a new timeframe is reached, the arrival rate is adapted. Concerning the availability of excess capacity, a random value is generated from the corresponding statistical distribution at the beginning of each timeframe outlined in Table IV.2-3. This random value represents the waiting time until the request can be executed externally; this is used by the routing algorithm to determine the processing costs of external execution. Repeating a simulation run 800 times, the risk of waiting times in case of using excess capacity is considered when determining the optimal in-house capacity.

Incoming requests characterized as *special requests* cannot be routed to the ECM; they are routed straight to the in-house unit (specifically, the waiting queue in front of it). For *regular requests*, the routing algorithm determines the current processing costs of both paths and then routes the request to the path with lower costs. The processing costs of the in-house execution thus result only from the SLA with the retailer; there are no variable costs connected with the in-house unit, and all fixed costs are sunk costs, which hence must not be taken into account. Regarding the SLA, costs can occur in two different ways: if a request cannot be processed ahead of the final processing deadline, the penalty has to be considered in the processing costs. Otherwise, if the agreed-upon processing time per request is exceeded, compensation costs per minute are charged. For the external execution, the processing costs consist of the variable cost per request and the costs resulting from the SLA determined analogously.

IV.2.4.4 Determining the Cost Advantages of Excess Capacity

Performing the discrete event simulation *with* and *without* the opportunity to use excess capacity reveals the cost advantages of the ECM (scenario 1). The relation between total costs and assigned in-house capacity is shown in Figure IV.2-5.

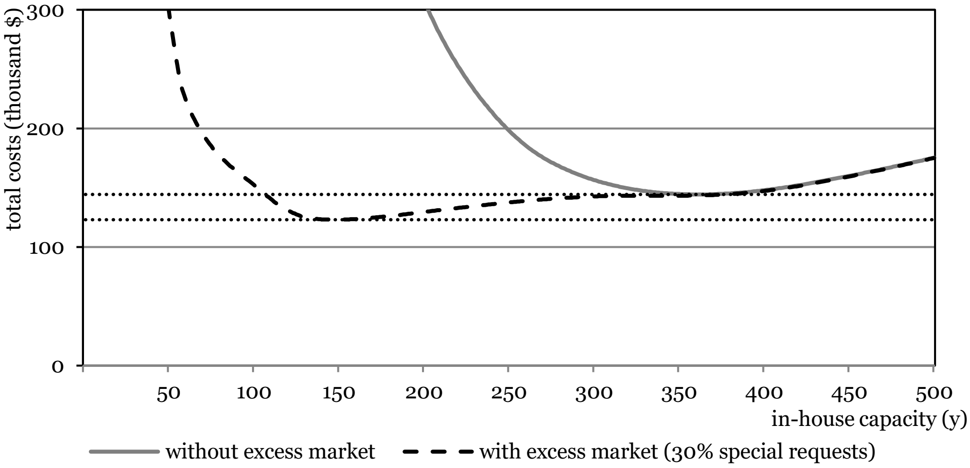

Figure IV.2-5 Total costs with and without excess capacity

The minima of both cost patterns (indicated by the dotted lines) represent the optimal level of capacity within the in-house unit. The optimal level of capacity *without* access to the ECM is reached at 362 units, corresponding to total costs of $144,292 per day, while the optimal level of capacity *with* access to the ECM equals 147 units, corresponding to total costs of $122,982 per day. Thus, total costs can be reduced by $21,310 (14.77%) per day if the ECM was available, although the sourcing of special requests is rejected a priori. In Figure IV.2-5, this cost advantage is indicated by the distance between the two dotted lines.

An analysis of the functions that sums up to the total costs (i.e., fixed costs for in-house capacity, variable costs for requests routed to the ECM, compensations and penalties for exceeding the agreed SLA) reveals the following:

For the scenario *without* ECM integration, very small in-house capacity produces long waiting times, and the total costs are high due to the corresponding SLA-induced compensations and penalties. With increased in-house capacity, more requests can be processed ahead of the final processing deadline; thus, total costs decrease drastically due to the fewer violations of the agreed-upon SLA processing time of 26:00 minutes and fewer requests exceeding the final processing deadline. Regarding the optimal level of capacity *without* access to the ECM (362 units), as indicated in Figure IV.2-5, no further cost savings are possible beyond this point, as the costs of additional capacity exceed the cost savings from it.

By contrast, in the scenario *with* ECM integration, the possibility of using excess capacities reduces the risk of exceptionally high SLA-induced compensations and penalties because the ECM allows the execution of regular requests that are left unexecuted in the other scenario. The high penalty for unexecuted requests ensures that the routing algorithm chooses the external execution path. Furthermore, as regular requests arriving in peak times (e.g., the early morning or evening) can be routed to the ECM, the waiting times in the queue in front of the in-house unit are reduced. Overall, special requests also benefit from excess capacities, as the waiting time in front of the in-house unit and the corresponding waiting compensations are reduced. Again, with the increased in-house capacity, waiting costs decrease to the point where the costs of additional capacity exceed the waiting-cost savings (147 units).

Thus far, we have used a percentage of 30% of authorization requests that require specialized interventions or customer callbacks due to incomplete or inaccurate registration forms in our simulation. However, this percentage may vary depending on the service considered. For example, the number of data required for the identification and authorization service, its complexity (e.g., dependencies between data packages) as well as the target group of the service (e.g., retailer focuses on customers with little online experience) can strongly influence the error rate induced by the user. To examine the influence of the number of incoming special requests, we vary the percentage of special requests while all other parameters are kept at their initial values.

Figure IV.2-6 summarizes the total costs assuming different percentage rates for special requests. The costs when employing the optimal level of in-house capacity combined with the ECM are lower for each setting (e.g., 10%, 30%, 50%) than in the solution without external service providers.

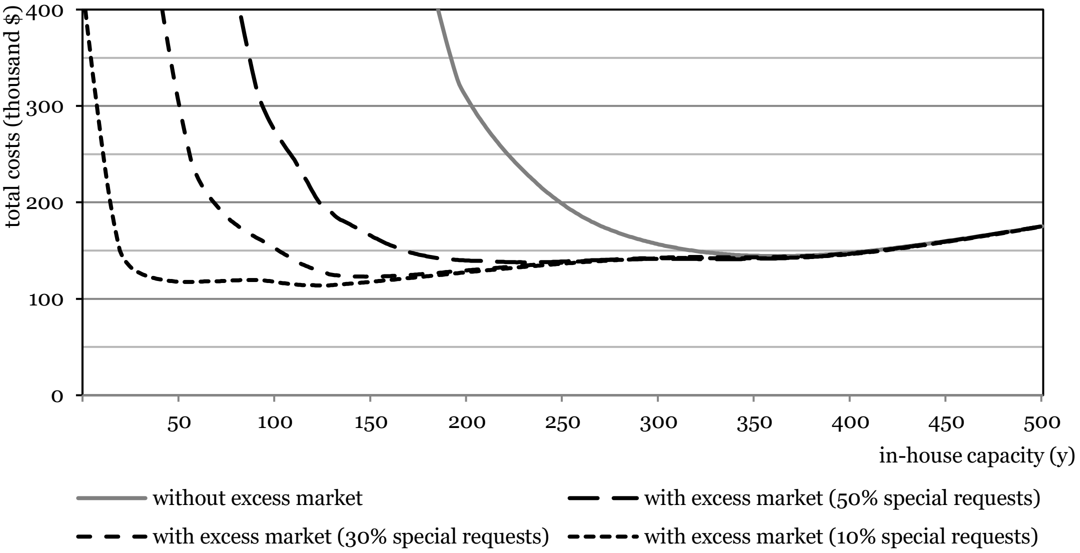

Figure IV.2-6 Cost patterns for different percentage rates for special requests

This *general cost advantage* can be explained the following way. In the scenario without ECM integration, all requests (whether regular or special) must be processed by the in-house unit, which leads to the cost disadvantages mentioned above. Likewise, in the scenario with ECM integration, a PSP would have to process all requests in-house if they were all categorized as special. Thus, the scenario without ECM integration corresponds exactly to a setting of 100% special requests, as, in both scenarios, the PSP has to execute all requests in-house. Accordingly, the optimal setting with ECM integration is preferable for all levels of special requests to the optimal setting without ECM integration. This is caused, inter alia, by the fact that ECM integration involves only the variable costs for each request sent to external providers. Accordingly, integrating excess capacity enables a general cost advantage which, however, decreases by the percentage rate of special requests. Table IV.2-4 summarizes this general cost advantage by presenting both optimal in-house capacity and the associated costs for the different percentage rates of special requests as well as the corresponding cost advantages compared to the scenario without ECM utilization.

	w/o ECM	**w/ ECM (10% SR)**	**w/ ECM (30% SR)**	**w/ ECM (50% SR)**
Optimal In-house Capacity [units]	362	125	147	233
Total Costs [USD]	144,292	113,665	122,982	137,808
Cost Advantage [%]	-	21.23	14.77	4.49

Table IV.2-4 Cost advantages for different percentage rates of special requests (SR) with ECM access compared to the scenario without ECM access

So far, we have identified a general cost advantage for the PSP as an opportunity to gain a competitive advantage by using ECM. In a cost-driven market environment, this cost advantage can be used for price differentiation on the side of the PSP to establish price leadership. However, based on the innovative opportunities of the on-demand integration of excess capacity, further strategies for gaining competitive advantages become evident. In the following, we therefore analyze how cost leadership can be used to create differentiation advantages besides that of price in competitive cost-driven markets.

IV.2.4.5 Determining the Differentiation Advantage of Excess Capacity

By pursuing a differentiation strategy, the PSP can create a unique selling proposition aside from cost leadership. Due to the cost-effective processing of requests via ECM, the PSP can use its cost advantage to create a variety of differentiation advantages; the PSP can distinguish its services regarding qualitative benefits and offer more cost-intensive services, while the cost advantage of ECM ($21,310 in our simulation) allows equal-cost market competition. In the following, we demonstrate differentiation strategy options and examine their benefits.

The starting point of our consideration is the model parameters set forth above. We employ the basic setting of our simulation (30% special requests). Furthermore, we consider parameters representing qualitative aspects for differentiation opportunities. For example, the PSP can offer an improved service level, meaning that it commits to a shorter processing time for incoming requests (scenario 2). Alternatively, the execution time the in-house unit spends on special requests can be expanded, allowing the in-house unit more time to increase the processing quality for special requests (scenario 3). For both differentiation strategies, we now determine to what extent a PSP *with* access to excess capacity can improve its service quality and thereby develop a substantial differentiation advantage.

In scenario 2, we examine the reduction of the agreed-upon SLA processing time in order to identify a lower limit for it. The benchmark for this optimization is represented by a competitor *without* access to excess capacity. First, we gradually reduce the SLA processing time (starting at 26:00 min) and determine the minimum of the total costs for each level of SLA processing time. Each experiment consists of 800 simulation runs. This is repeated until the minimum of the total costs of the PSP *with* access to the ECM equals the minimum of the total costs of the competitor *without* access to the ECM. Figure IV.2-7 shows the cost patterns leading to identical costs. According to this staged optimization approach, the PSP *with* ECM access can offer an SLA processing time of 10:54 minutes (as a lower limit) instead of 26:00 minutes while realizing the same total costs as a competitor *without* ECM access. This means that the PSP can offer an SLA that is 58% stricter at an identical price. Accordingly, any SLA between 26:00 and 10:54 minutes generates both differentiation advantages (a more attractive SLA) and cost advantages (the remaining cost benefit) when utilizing ECM.

In scenario 3, we use the same staged optimization approach to determine the upper limit of the extra time the in-house unit can spend on special requests. Starting with our basic simulation setting, we gradually increase the processing time for special requests (starting at 12:00 minutes) until the minimum of the total costs of the PSP *with* access to the ECM equal the costs of the competitor without it. As shown in Figure IV.2-8, the PSP can increase the processing time for requests by 4:13 to 16:13 minutes (upper limit). Consequently, the in-house unit has about 35% more time for correcting and post-processing and for contacting customers to complete identification and authorization procedures.

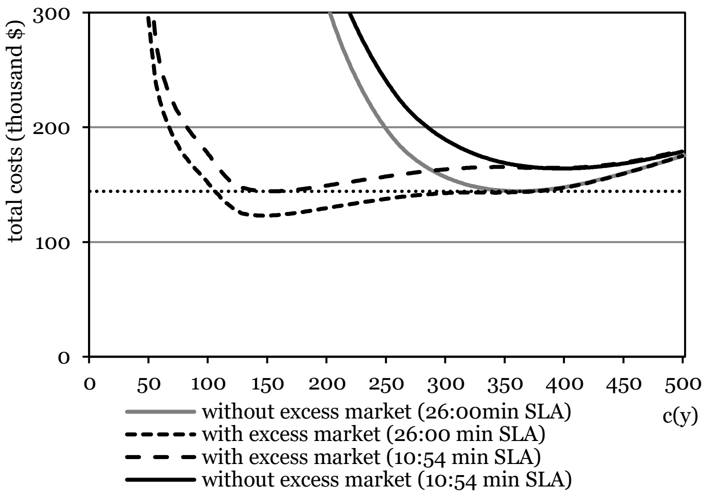

Figure IV.2-7 Improved SLA

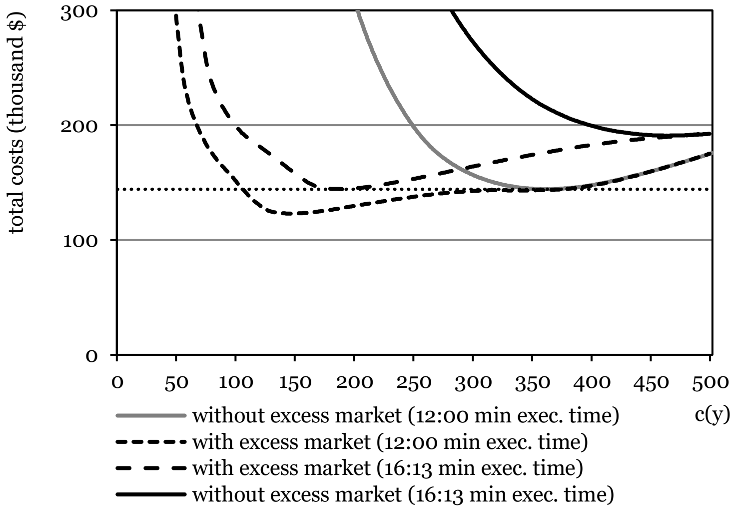

Figure IV.2-8 Increased Execution Time

Table IV.2-5 provides details on the differentiation advantages illustrated in Figure IV.2-7 and Figure IV.2-8 by specifying the total costs of scenarios 2 and 3, their cost components, and the shifting of the cost advantage (shown in brackets) compared to the basic setting with ECM access (scenario 1). It considers the costs for the in-house unit, the costs for excess capacity, compensations, and penalties. For the sake of completeness, the setting without ECM access (benchmark) is shown in the far-right.

Cost component	**Improved SLA of 10:54 min (scenario 2)**	**Increased exec. time of 16:13 min (scenario 3)**	**Basic setting w/ ECM (scenario 1)**	**Basic setting w/o ECM (benchmark)**
Optimal In-house Capacity [units]	154	189	147	362
In-house Capacity Costs [USD]	53,900 (+2,450)	66,150 (+14,700)	51,450	126,700
Excess Capacity Costs [USD]	41,410 (+442)	42,195 (+1,227)	40,968	0
Compensations and Penalties [USD]	48,982 (+18,418)	35,947 (+5,383)	30,564	17,592
Total Costs [USD]	144,292 (+21,310)	144,292 (+21,310)	122,982	144,292

Table IV.2-5 Summary of costs and cost components for different scenarios

In scenario 2, the PSP can offer a more attractive SLA and, at the same time, face higher compensation payments due to the reduction in the agreed-upon SLA timeframe. Thus, most of the cost advantage of ECM integration is passed on to the retailer. However, the PSP has to consider possible negative side effects on customer (i.e. retailer) perception caused by increasing SLA-violations, which are not included in our model. Accordingly, the improved SLA of 10:54 minutes represents the absolute minimum of the processing time and does not contain any concrete action recommendation. To emphasize the advantages, we further examined the optimal level of capacity *without* access to the ECM with the corresponding SLA processing time of scenario 2 (10:54 minutes). The optimal level of capacity *without* access to the ECM and a SLA processing time of 10:54 minutes is reached at 399 units, corresponding to total costs of $164,136 per day.

In scenario 3, longer execution times for special requests require more in-house capacity, and compensation payments between the PSP and the retailer increase. However, as the PSP's in-house unit is given more time to focus on non-standard procedures, processing quality can be increased. Though quality and customer satisfaction are, as indicated, not captured in our model, we assume that increased processing times can be utilized to respond individually to customer needs, thereby strengthening customer relationships. Thus, the differentiation strategy of scenario 3 can constitute a significant competitive advantage for the PSP, as it may increase customer satisfaction as well as the retailer's prospects for customer retention. Analogous to the underpinning of the advantages of scenario 2 the optimal level of capacity *without* access to the ECM with the corresponding execution time (16:13 minutes) is reached at 464 units, corresponding to total costs of $190,927 per day.

Based on the previous advantage analysis of ECM, we conduct a more detailed analysis of the application of ECMs in different digitized business processes to investigate strategic implications of ECM.

IV.2.4.6 Detailed Cost Analysis for Different Process Types

To further analyze our model and to ensure its applicability to real-world strategic decisions we analyze the use of an ECM in different possible digitized business processes by considerably fluctuating model parameters around the values of the initial scenario. Therefore, we choose parameterizations that differ in terms of their *degree of criticality*, concerning the SLA-induced compensations, as well as in terms of the *degree of specialization*, concerning different percentage rates of special requests. By changing the parameterization of the agreed-upon SLA compensation to either $\$0.02 * (minutes\ exceeded)^{1.25}$ or $\$0.07 * (minutes\ exceeded)^{2.25}$ (low or high degree of criticality) while simultaneously changing the percentage rates of special requests to either 10% or 50% (low or high degree of specialization), we obtain four different digitized business processes (cf. Table IV.2-6). Performing the discrete event simulation *with* and *without* the opportunity to use excess capacity reveals the advantages of the ECM and, thus, its strategic implications on business strategy. Depending on their business model and the associated processes, one or more of the analyzed business processes may be relevant for companies. With the help of the insights gained from the simulation, it can be deduced for which of a company's processes - measured in terms of the request's degrees of criticality and specialization - the potential of integrating excess capacity is worthwhile to create competitive strategic advantages. Table IV.2-6 summarizes the results for the different processes by presenting the respective parametrization, the optimal in-house capacity, the associated costs for the different percentage rates of special requests as well as the corresponding cost advantages compared to the scenario without ECM utilization. The corresponding relation between total costs and assigned in-house capacity is shown in Figure IV.2-9.

	Process 1		Process 2		Process 3		Process 4	
Exemplary process	**bank account relocation service**		**automated credit assessment and credit decision-making**		**Master data and address data change**		**payment transaction processing**	
	w/o ECM	**w/ECM**	**w/o ECM**	**w/ECM**	**w/o ECM**	**w/ECM**	**w/o ECM**	**w/ECM**
Degree of Specialization	High		High		Low		Low	
Special requests	50%		50%		10%		10%	
Degree of Criticality	Low		High		Low		High	
SLA compensation	$\$0.02 * (minutes\ exceeded)^{1.25}$		$\$0.07 * (minutes\ exceeded)^{2.25}$		$\$0.02 * (minutes\ exceeded)^{1.25}$		$\$0.07 * (minutes\ exceeded)^{2.25}$	
Optimal In-house Capacity [units]	247	247	467	430	247	153	467	107
Total Costs [USD]	112,653	112,653	168,030	166,186	112,653	110,230	168,030	131,170
Cost Advantage [%]	-	0.00	-	1.09	-	2.15	-	21.94

Table IV.2-6 Cost advantages for different processes

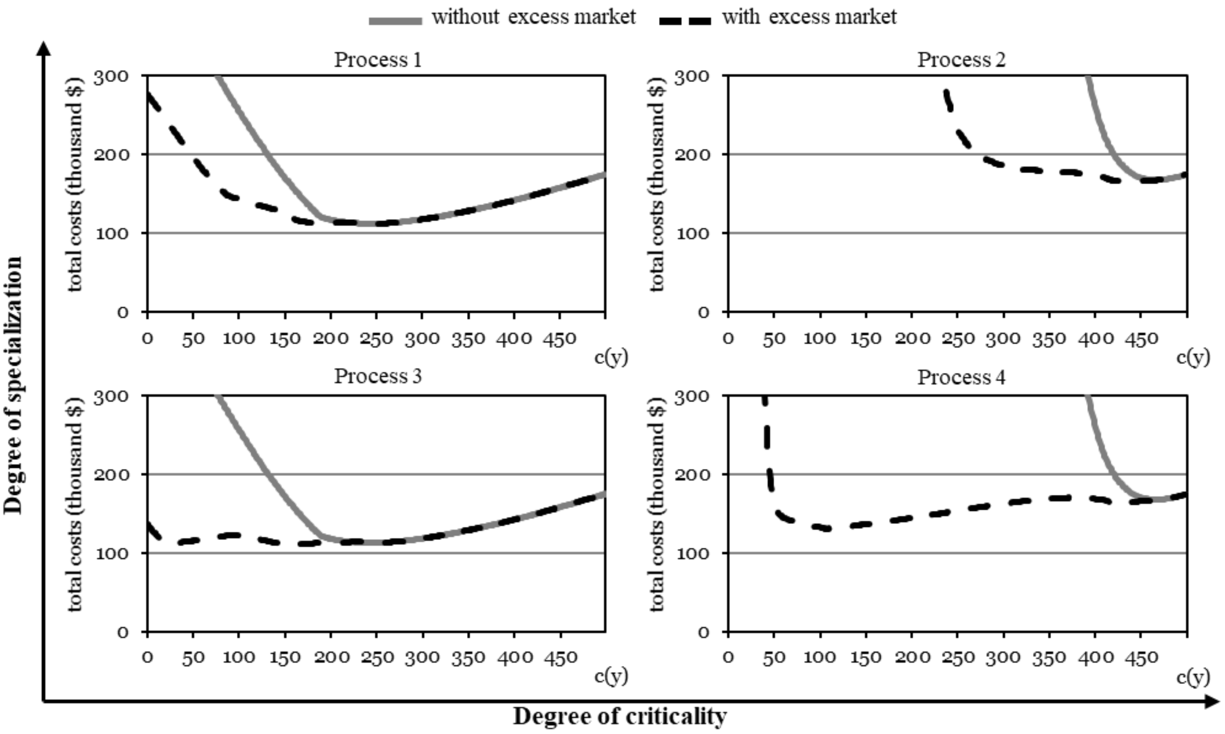

Figure IV.2-9 Overview of results for different digitized business processes

For a process with a *high degree of specialization* and *a low degree of criticality* (Process 1), we consider exemplarily a bank account relocation service which is offered to new customers of a bank to relocate all their existing contracts with other institutions to the new bank. This service is characterized by a high degree of specialization as the correctness of all entered data is essential and the bank products to be relocated have a low degree of standardization, which may lead to frequent inquiries being made to the customer. A low degree of criticality is reasonable since the relocation service is not extremely time-critical and does not lead to critical problems or discomfort for the customer, at least in the short term, if the SLA deadline is exceeded. The optimal level of capacity for this process *without access as well as with access* to the ECM is reached at 247 units, corresponding to total costs of $112,653 per day. Thus, in this process, integrating excess capacity would not result in any cost advantage for the optimal in-house capacity level. However, in terms of total costs, a downside deviation from the optimal in-house capacity, i.e. a very small in-house capacity that produces long waiting times, is more critical in a scenario without ECM integration than in a scenario with ECM integration. As the total costs in the scenario with ECM integration are always equal to or lower than in the scenario without ECM integration, regardless of the capacity selected, an integration of the ECM also offers an advantage here, since the optimal capacity in a real world setting is difficult to determine exactly or can fluctuate slightly on a daily basis.

An example for our second process with a *high degree of specialization* and a *high degree of criticality* is the automated credit assessment and credit decision-making. Since the correctness of the data is essential, but at the same time divergent non-standardized input is collected from the customer in the application process, this leads to a high number of special requests and a high degree of specialization. On the other side, it is essential to process the requests in time to avoid the loss of customer interest. The optimal level of capacity *without* access to the ECM is reached at 467 units, corresponding to total costs of $168,030 per day, while the optimal level of capacity *with* access to the ECM equals 430 units, corresponding to total costs of $166,186 per day. In contrast to process 1, the total costs can at least be reduced minimally by $1,844 (1.09%) per day if the ECM was available. Even an ECM integration doesn’t offer a high cost advantage, analogous to process 1, the ECM integration nevertheless offers a strategic planning advantage since total costs in the scenario with ECM integration are always equal to or lower than in the scenario without ECM integration and, therefore, it is less critical to determine exactly optimal in-hose capacity.

An example process for our third case example with a *low degree of specialization* and a *low degree of criticality* is a change request to the stored customer master data, such as a change of address. This process is characterized by a low degree of specialization as most of the conceivable requests are standardized, which may lead to rare inquiries being made to the customer. Furthermore, as these requests are usually not time-critical and have no direct influence on customer satisfaction, a low degree of criticality is reasonable. Analogous to our first process, optimal level of capacity for this process *without access* to the ECM is reached at 247 units, corresponding to total costs of $112,653 per day. The optimal level of capacity *with* access to the ECM equals 153 units, corresponding to total costs of $110,230 per day which would lead to cost reduction of $2,423 (2.15%) per day if the ECM was available. Similarly, as with the two previous processes, an integration of the ECM offers at first sight no significant cost advantage. However, as we can observe in the corresponding figure, the ECM integration offers an extremely high strategic planning advantage since total costs in the scenario with ECM integration are always lower than in the scenario without ECM integration. Particularly in the range between 0 and 247 units, the total costs *with access* to the ECM are significantly lower and range between $110,230 (247 units) and $135,510 (0 units). Thus, a selected in-house capacity aside from the optimum would always show a cost advantage with an integration of the ECM. For example, the costs for a capacity of 50 units corresponding sum up to total costs of $364,117 for a scenario *without access* to the ECM and $114,457 for a scenario *with access* to the ECM.

Similar to our initial authorization process case, we assume in our last analyzed case a payment transaction processing process with a *low degree of specialization* and a *high degree of criticality*. However, in contrast to our initial authorization case, we assume an even more critical process, which is related to the higher agreed-upon SLA compensation. The optimal level of capacity *without* access to the ECM is reached at 467 units, corresponding to total costs of $168,030 per day, while the optimal level of capacity *with* access to the ECM equals 107 units, corresponding to total costs of $131,170 per day. In contrast to the previous three processes the total costs can be significantly reduced by $36,860 (21.94%) per day if the ECM was available. For this process, an integration of the ECM delivers not only a strategic planning advantage but also a significant cost advantage. As illustrated in the corresponding figure, the total costs *with access* to the ECM are lower for all selected in-house capacities aside from the optimum significantly, especially in the range between 50 and 467 units. In conclusion, we can state from our cost analysis for different process types that an integration of ECM offers advantages for different types of digitized processes in terms of their *degree of criticality and specialization*. A strategic planning advantage is evident for all examined types of processes but especially for processes with a low degree of specialization. This indicates that the total costs of an ECM integration are always lower or at the most equal to the total cost of an ECM integration – even if the exact optimal in-house capacity has not been determined. Since the parameterizations of individual components of our model are not precisely determinable and / or are volatile in a real-world scenario, the exact determination of the optimal in-house capacity is not feasible. In addition, we further observe a significant cost advantage for processes with a *low degree of specialization* and a *high degree of criticality.* Measured in terms of cost advantage and strategic planning advantage, the ECM integration should be implemented in a company in the following prioritization: Processes with a (1) low degree of specialization and high degree of criticality (2) low degree of specialization and low degree of criticality (3) high degree of specialization and high degree of criticality (4) high degree of specialization and low degree of criticality.

IV.2.5 Conclusion, Managerial Implications, and Further Research

Amid the challenges for service providers in cost-driven value chains and the research gap described above, this paper examines the potential of IT-enabled ECM to create *competitive advantages* in e-business value chains for *inhomogeneous* services. Having discussed the information and integration capabilities necessary to utilize excess capacity, we considerably extended the model of Dorsch and Häckel (2012a) and focus on the capacity optimization problem of a BPSP within a three-stage supply chain. We ran a discrete-event simulation with input data from a possible application scenario to analyze the model and derive interpretable results relevant to our research question.

We answered our research question by analyzing the competitive advantages that can be realized through an IT-enabled ECM for the processing of cost-driven inhomogeneous service requests. First, we identified a remarkable *cost advantage* in using the ECM to process a certain portion of incoming requests in different types of digitized business processes, as the capacity of the in-house unit can be reduced without negative effects on service levels, reducing overall operating costs. Our analysis reveals a cost advantage even if the portion of special requests is rather high (i.e., if the portion of incoming requests suitable for handling by third-party providers is low). Nevertheless, the extent of this competitive advantage is rising significantly with the increasing service homogeneity. Building on this *cost advantage*, we examined the possibilities of gaining a *differentiation advantage* (i.e., improvements in service levels and service quality without raising prices). We showed that reduced processing times can be guaranteed and executions times (and thus quality) increased at equal costs, leading to a competitive advantage.

Based on these results, we can derive the following managerial implications:

- First, our results suggest that high upfront investments in information and integration capabilities might pay off in the mid to long run due to the economic potential of using excess capacity. The quantitative results of our model show the potential value of such investments and therefore determine an upper bound for investment spending.

- Furthermore, our model provides a sound basis for analyzing the economic advantages of various differentiation strategies. As discussed, the BPSP can, for instance, offer improved service levels and/or higher service quality without raising prices. Our model allows a thorough evaluation of these different business strategies, which might strengthen a BPSP's competitive position.
- As discussed in the introduction, an IT-enabled ECM is most suitable for standardized services rather than complex or non-standardized services. Regarding the processing of these, we propose that a BPSP should carefully evaluate whether investments in the further standardization of services may enable the usage of external service providers such as IT-enabled ECM and whether the resulting economic potential would justify such investments.
- Furthermore, as discussed, the extent of the competitive advantages of an IT-enabled ECM is highly dependent on the inhomogeneity of the service. As a consequence, a BPSP may also consider investments into a further homogenization of the service (e.g., by improving the usability of input forms, thus enhancing the data quality of the incoming service requests) to strengthen the potential competitive advantages.
- To look ahead, a BPSP might also consider establishing new business models connected to excess capacity that consider offering non-SLA backed capacity only or operating as excess capacity brokers or market makers. Highly standardized services, especially those spanning multiple business sectors, may offer strong potential for such business models.

Although our model implies several managerial implications, it also has limitations based on its assumptions, which offer opportunities for future research. We relied on the simplifying assumption of an *exogenous market*, in which the amount of the available excess capacity is not affected by the actual demand of the BPSP or any other market user. Moreover, the interdependencies between peak times both for the BPSP and the market players were not considered. Consequently, modeling an endogenous market may be a promising subsequent step from an *analytical point of view*. Additionally, from an *empirical point of view,* the lack of knowledge concerning the interdependencies between the strategy of a single player and an endogenous ECM should be addressed by appropriate field studies. Moreover, our model focuses on cost minimization, which seems a reasonable first step, as our study is concerned with the analyses of cost-driven services. Nevertheless, our analyses of possible differentiation advantages are limited to a discussion of the differentiation strategies that build on cost advantages and that can be realized without raising prices. Extending the model by incorporating price-demand functions (and thus considering revenue aspects) would facilitate a further analysis of various competitive differentiation strategies and their economic potential.

Aside from these potential starting points for further research, our paper contributes to the knowledge on the competitive advantages that can be realized through IT-enabled ECM within a BPSP`s value chain for the processing of cost-driven inhomogeneous service requests. Our research provides valuable insights for both researchers and managers engaged in business processes and service management.

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V Summary, Results, Future Research, and Conclusion

This Chapter contains an executive summary as a preliminary remark in Section V.1, the key findings of this doctoral thesis in Section V.2, and an outlook on future research areas in Section V.3. It also provides a short conclusion in Section V.4.

V.1 Executive Summary

The overarching objective of this doctoral thesis was to contribute to the field of Finance and Information Management by providing novel perspectives on digital transformation and IT innovation management. After motivating the relevance of developing new management and evaluation approaches, this thesis presented new approaches that support the digital transformation and IT innovation management. Three relevant challenges were addressed in the research papers that are included in this doctoral thesis:

(i) Digital Transformation Management
(ii) IT Innovation Management
(iii) Analysis of Specific IT Innovations

Regarding the first challenge, research paper P1 supports an organization wide digital transformation management by means of providing a multi-dimensional maturity model that enables a holistic view an all organizational levels and capabilities affected by digital transformation (Chapter II).

Regarding the second challenge, research papers P2, P3, and P4 support an economically well-founded IT innovation management by providing tailored quantitative approaches that enable to optimize the team design of IT-related projects as well as to determine the development path and strategies for investments in IT innovations (Chapter III).

Regarding the third challenge, research papers P5 and P6 support an economically reasonable analysis of specific IT innovations by means of providing tailored qualitative and quantitative approaches that enable to determine and analyze the benefits and competitive advantages of specific IT innovations (Chapter IV).

V.2 Results

In the following, the key findings of the research papers of this doctoral thesis are presented. Subsequent, future research opportunities are discussed in Section V.3.

V.2.1 Results of Chapter II: Digital Transformation Management

In Section II.1, research paper P1 identifies and structures the dimensions affected by digital transformation on all organizational levels (Objective II.1). Based thereon, the paper provides a capability-oriented development path towards digital maturity for all organizational dimensions affected by digital transformation (Objective II.2). Following an established procedure model (Becker et al. 2009), a digital transformation maturity model (DTMM) is deductively and inductively derived by conducting a structured literature review and focus group discussions. The final DTMM comprises organizational capabilities with respect to 26 dimensions (e.g., *Customer Insights, Pricing Strategy, Production Flexibility, Workplace Environment, Data Collection, IT Security*) that are clustered into six focus areas (*Customer*, *Business Model*, *Process*, *People & Culture*, *Data*, and *Infrastructure*). Depending on the respective dimension, each dimension contains 4 to 6 capabilities. Even though none of the capabilities within a specific dimension is per se ‘better’ than another one, the acquisition of capabilities contributes to digital maturity since organizations have the freedom to choose the most appropriate among their acquired capabilities for a specific context. Exemplary, the dimension *Customer Insight*, clustered into the focus area *Customer*, contains the four capabilities *No Information*, *Anonymous Information*, *Segment-specific Information*, and *Personalized Information.* As the dimensions and focus areas are interrelated, organizations need to introduce an organization-wide transparent and accepted digital transformation (DT) strategy, which is aligned with the organizational purpose and other organizational strategies (Matt et al., 2015). The detail level of the DTMM extends high-level transformation paths and maturity models (e.g., PWC 2016; Matt et al. 2015) as they provide rather a foundation for initially grasping the topic of DT, but lack a deep-dive into DT dimensions and capabilities. The DTMM adds to descriptive knowledge on DT and serves practitioners as a profound basis to capture their organization’s status quo concerning DT, to derive their future target state and associated capabilities within each dimension and focus area.

V.2.2 Results of Chapter III: IT Innovation Management

Chapter III provides support towards economically well-founded IT innovation management and examines three research topics with the help of tailored quantitative evaluation approaches.

In Section III.1, research paper P2 improves the value contribution of IT-related innovation projects (ITIP) by providing a value-based, ex-ante evaluation approach that allows for optimizing their team design in the innovation creation phase by considering different team design factors (Objective III.1). P2 is based on a normative analytical modeling approach (Meredtih et al. 1989) and refers to findings from previous research on project team effectiveness, team design, and IT innovations. Generally, the results of the model show that a well-designed team considering the ITIP characteristics can contribute to reducing the risk of negative profit that might occur in case of somewhat arbitrary decisions on team design. More specifically, the analysis of the model showed that only about a fourth of the random team designs resulted in a positive profit. In return, the well-founded, optimal team designs determined using our model led to a positive profit in 95% of all cases. With a focus on some of the individual team design factors, the analysis demonstrates that an ITIP team should be formed of around 6 to 11 people, and they should be neither extraordinarily heterogeneous nor homogeneous regarding their academic background to achieve an optimal ITIP profit. Further, an ITIP team should have high mean work experience, optimally in the range of 22 to 30 years, to be able to realize the maximal ITIP profit. Thereby, the team size is a crucial design parameter as deviations from the optimal solution will quickly result in a considerably lower or even negative ITIP profit. This finding is in line with previous research, which shows that small teams lack the diversity needed for innovation and that large teams, in contrast, hamper effective interaction, information exchange, and participation due to a rising communication complexity between team members (West and Anderson 1996; Zenger and Lawrence 1989). The paper contributes to practice and academic research by combining a broad range of research in the field of team design, team performance, and IT innovation projects to a value-based, ex-ante evaluation approach and serves as a basis for further practical evaluation.

In Section III.2, research paper P3 identifies the developmental path of technologies and explores the relationship between scientific and practice-oriented research (Objective III.2). Therefore, a quantitative method for investigating hype surrounding technology trends and the interest of industrial and scientific researchers over time was developed. A self-developed automated webscraper collected vast amounts of paper and patent publication data on 15 technologies. Next, the data were prepared for analysis by eliminating duplicates and conversing the datasets into the necessary format for the subsequent data analysis. Plotting the data exhibited a resemblance to the patterns of the hype cycle model. Subsequently, the data were analyzed by methods of time series analysis (ARMA and ARMAX) to analyze time series graphs and predict the future. The predictions of all models have a mean squared error smaller or equal to 0.0038 for the models trained on the paper time series and a mean squared error smaller or equal to 0.00093 for the models trained on the patent time series. Based on the analysis, the paper states that academic researchers appear to be leading in adopting emerging technologies and innovations, later followed by their counterparts in practice-oriented research, which show a stronger peak of interest. Although our analysis shows a resemblance to the patterns of the hype cycle model, the ideal hype curve, as outlined by Gartner's Hype Cycle, could not be achieved as multiple peaks could be observed regularly, which is in line with previous findings (Campani and Vaglio 2015; Cryer and Chan 2008). Beyond the time series analysis, the ARMA model has proven its prediction qualities for paper and patent publication curves, exhibiting low mean squared errors. The results serve as a basis for organizations to improve their technology development assessment, e.g., when deciding on an appropriate investment. Furthermore, the paper provides a basis for further research, which may be directly used in decision support, e.g., to anticipate the success probabilities of specific technologies.

In Section III.3, research paper P4 provides a quantitative optimization model for the determination of an optimal budget allocation in the sense of maximizing the investment´s overall NPV. Thereby, the model considers relevant influencing factors and the timing of possible investments (Objective III.3). Thus, P4 supports organizations in the management of investments in emerging IT innovations, more precisely whether to invest at an early stage as a *first mover* (FM), in a later stage as *late mover* (LM) or to pursue as “mixed” strategy, in terms of timing and investment volume, that may outperform strict FM or LM strategies (Swanson and Ramiller 2004). Generally, the paper shows that strict investment strategies are often disadvantageous, that the amount of the investment budget influences the innovation´s expected net present value (NPV), and that the company's innovativeness has the most substantial influence on the innovation budget allocation. Moreover, the analysis shows that a mixed investment strategy is usually favorable compared to a strict FM or LM investment strategy. In most cases, it is advantageous to invest part of the innovation budget in emerging IT innovations, which substantially corresponds to earlier qualitative and empirical studies by Wang (2010), Lu and Ramamurthy (2010), or Dos Santos and Pfeffers (1995). In more detail, it is quantitatively demonstrated that in most cases a below-average innovative company should preferably choose a rather LM strategy and an above-average innovative company should instead choose a FM strategy. Further, a company with a large budget at its disposal should rather choose a LM strategy, except if it is above-average innovative and the IT innovation is a disruptive one. In contrast to that, a company with a small budget at its disposal should instead choose a FM strategy if it is above-average innovative and a LM strategy if it is below average, which supports findings from Hoppe (2000). Concerning IT innovation-specific factors, for somewhat disruptive IT innovations, a FM strategy is advantageous. In conclusion, P3 contributes to one of the fundamental research questions in IT innovation literature of *when* and *to what extent* a company should invest in an emerging IT innovation.

V.2.3 Results of Chapter IV: Analysis of Specific IT Innovations

Chapter IV focuses on the analysis of specific IT innovations. One the one hand, Chapter IV focuses on the manufacturing sector by exploring the benefits of technologies behind the term Industry 4.0, such as internet of things or cyber physical systems. On the other hand, Chapter IV examines the potential of IT-enabled excess capacity markets for business process service providers in cost-driven e-business environments.

In Section IV.1, research paper P5 identifies and structures the anticipated benefits of digital technologies in the context of manufacturing organizations (Objective IV.1). The conducted structured literature review is in line with established methods concerning structured literature reviews in the information system (IS) field (e.g., Bandara et al. 2011; Fettke 2006; vom Brocke et al. 2009; Webster and Watson 2002). The 365 identified benefits were consolidated to 24 conclusive benefits, e.g., *production flexibility, continuous improvement,* or *coping with demographic change* and structured into the four dimensions *operational, managerial, strategic,* and *organizational*, using an established framework for IS benefits (Shang and Seddon 2002). In addition to the framework, different managerial implications and challenges were discussed to address Objective IV.1. First, the structured processing of benefits revealed that not all benefits are independent of each other. Especially benefits on the operational level often serve as the basis for the realization of benefits on the managerial or strategic level (e.g., the realization of strategic benefits like the alignment of production to changing, individual customer demands requires the realization of production flexibility or an accelerated product development process). Accordingly, the manifold interdependencies must be considered by management in terms of cause-effect relations to determine which benefits are intertwined and to identify all benefits resulting from the implementation of certain enabling technologies. Second, the line between operational and managerial benefits for certain benefits rather vanishes, especially regarding the production system. This influences traditional planning processes and requires management to adapt managerial processes. Third, current research on Industry 4.0 focuses primarily on conceptual work and rarely discusses actual test-beds and guidance on how to realize specific benefits by means of enabling technologies. Therefore, organizations need to determine concrete investment measures and transformation roadmaps in the course of their digitalization strategy. In sum, P5 enables decision makers to identify relevant fields of actions, to develop comprehensive business strategies, and consequently, to derive value from the realization of Industry 4.0 investments.

In Section IV.2, research paper P6 examines the potential of IT-enabled excess capacity markets (ECM) to create competitive advantages in e-business value chains by analyzing a business process service provider’s (BPSP) capacity-related optimization problem within a three-stage supply chain (Objective IV.2). The paper evaluates this potential by building an analytical model based on queuing theory and a subsequent discrete-event simulation applying a possible application scenario. Firstly, the analysis identifies a remarkable cost advantage in using excess capacity as the in-house capacity can be reduced, even if the portion of special requests is rather high (e.g., if the portion of incoming requests suitable for handling by third-party providers is low). Thus, the capacity of the in-house unit can be reduced without negative effects on service levels, reducing overall operating costs. Secondly, building on this cost advantage, P6 furthermore identifies differentiation advantages. For example, the analysis showed that BPSP could guarantee reduced processing times and decrease execution times at equal costs (thus leading to improvements in service levels and service quality). Thirdly, P6 further analyzes the usage of an ECM for different possible digitized business processes. As a result of this analysis, measured in terms of cost advantage and strategic planning advantage, the ECM integration tends to be favorable for processes with a *low degree of specialization and a high degree of criticality* or a *low degree of specialization and a low degree of criticality*. Therefore, as a result of all analyses, the paper demonstrates that high upfront investments in information and integration capabilities might pay off in the mid to long run due to the economic potential of using excess capacity. Furthermore, our model serves as a sound basis for analyzing the economic advantages of various differentiation strategies (e.g., offering improved service levels and/or higher service quality without raising prices) and decision support for the usage of an ECM for different possible digitized business processes.

Based on the results of the research paper presented above, the following Section presents an outlook for future research that takes up the Chapters’ limitations and assumptions.

V.3 Future Research

V.3.1 Future research in Chapter II: Digital Transformation Management

In Section II.1, research paper P1 provides insights for managing digital transformation from a holistic organization perspective. However, the paper shows some limitations that present starting points for future research.

Firstly, the paper develops a digital transformation maturity model (DTMM) with focus areas and dimensions on an abstract level of granularity to create long lasting insights as it recognizes that digital technologies and the business environment will continuously evolve and change over time. However, due to rapid technological change, especially the specific capabilities in each dimension should be subject to continuous re-evaluation and adjustment in the future. Secondly, although the paper follows a procedure model and conducts a multi-methodological approach, i.e., by applying interviews with practitioners, the development of the DTMM might suffer from potential bias concerning literature selection and author's judgment. Hence, the DTMM might benefit from further validating activities by applying it in real-world scenarios. Lastly, specific digital transformation (DT) projects require to combine certain capabilities, and the DTMM does not consider any interdependencies between different capabilities. Hence, the DTMM could be extended through subsequent development by identifying interdependencies between dimensions and capabilities.

V.3.2 Future research in Chapter III: IT Innovation Management

The approach for the evaluation of IT-related innovation projects (ITIPs) related to their team design developed in research paper P2 (Section III.1) comes along with several limitations that represent areas for future research.

The model's influencing parameters are not comprehensive and the parameter determination was only shown exemplarily. Therefore, further research should consider an empirical evaluation within a given organizational context and assessments through experts or consultants based on experience from former investments (Meredith et al. 1989; Hevner et al. 2004; Wacker 1998). For example, further internal and external factors, like the company size, the risk attitude, and the business environment, should be regarded in future studies. Furthermore, simplifying and rather abstract assumptions like the actual interpretation of the benefit factors "New-to-Market" and "Fit-to-Market" and their conversion into a monetary outcome need further research. Following on from this point, a next step could be the investigation of further relevant benefit factors like "Time-to-Market" or "Cost-to-Market" in a holistic way. Lastly, a differentiation between innovation laggards, opportunistic adopters, and systematic innovators might provide a more detailed view onto the complexity of the desired IT innovation and its influence on the ITIP's optimal team design.

From an empirical point of view, the results of research paper P3 (Section III.2) imply a complex relationship between the work of academic researchers and their counterparts in practice-oriented research. However, the limitations of the paper must be taken into consideration and reveal new possibilities for future research.

First, the number of data sources for the subsequent analysis was limited to research papers and patent data. Therefore, the methodology may profit from more data sources and the introduction of new data types, like online search engine traffic or newspaper articles. Further, increasing the number of examined technologies might also promise to yield formidable results. Second, although the methods used for the analyses (ARMA(X)) are considerably more complex than most approaches from previous studies, a possible next step would be to apply more sophisticated machine learning approaches to the collected data. Based on that, these approaches could be used to derive predictions about the future development and success probabilities of technologies. Another interesting approach for further research is the role of academic and industrial researchers on the level of completed and institutionalized technologies. Understanding their role and interaction on this meta-level might help to understand their impact on each other and the innovation system.

Although research paper P4 (Section III.3) presents a new approach that considers relevant influencing factors regarding investments in an emerging IT innovation to determine optimal investment strategies, it is beset with several reasonable limitations.

The model and its findings may not be practically applicable without further analyzing the influencing input parameters. There are probably other critical influencing parameters like interdependencies with other technologies, which could be evaluated in an organizational context or using empirical data (Meredith et al. 1989; Hevner et al. 2004; Wacker 1998). Therefore, the determination and validation of input parameter values would also benefit from empirical and benchmark analyses or educated assessments. Subsequently, an analysis by sophisticated machine learning methods would further ensure an expedient data basis. Concerning the interdependencies with other technologies, a next step could be the development of an integrated portfolio approach that comprehensively depicts investments in different emerging IT innovations in a dynamic multi-period model. Further, the risks of the underlying IT innovations are only considered implicitly by two influencing factors, success probability and economic potential. Therefore, a next step could be the explicit consideration of risk and return profiles of emerging IT innovations.

V.3.3 Future research in Chapter IV: Analysis of Specific IT Innovations

The limitations of research paper P5 in Section IV.1 that provide opportunities for future research regarding innovations in the context of the term Industry 4.0 are the following.

The conducted structured literature review includes only benefits that are mentioned in scientific literature. Therefore, potential benefits that are not considered by researchers or findings only included in non-scientific publications are missing. To overcome this issue, further research should extend the research methodology accordingly for white papers or real-world application cases and conduct interviews with practitioners. Further, the paper does not consider any interdependencies between benefits, which represents a starting point for further research. A next step in this direction could be a hierarchy of benefits and cause-effect-chains that could display causal relations among complementary benefits by means of benefit dependency networks (Ward and Daniel 2006). Lastly, as Industry 4.0 is a relatively new field of research, there is almost no empirical evidence and, at the same time, considerable uncertainty in literature and practice about which of the anticipated benefits might genuinely become reality. Thus, the evaluation and quantification of benefits under consideration of risk and return aspects is another important topic for further research.

In Section IV.2, research paper P6 provides new insights for both researchers and managers engaged in the field of IT-enabled excess capacity markets within a business process service provider’s (BPSP) value chain. However, the presented approach shows some limitations that present starting points for future research.

The assumption of an exogenous market neglects interdependencies between the BPSP and other market players. Thus, from an analytical point of view, modeling an endogenous market may be a promising step for future research. Based on that, the interaction between strategies of different players in the market could be addressed. Empirical field studies may save as a basis for modeling an endogenous market and collect a profound data basis for different strategies. Furthermore, our model focuses on cost minimization and the analyses of possible differentiation advantages are limited to a short discussion of the differentiation strategies. Therefore, extending the model by incorporating price-demand functions should be addressed in future studies. Thereby, considering revenue aspects would facilitate further analysis of various competitive differentiation strategies and their economic potential.

In sum, the potential research opportunities outlined above may serve as starting points for further investigations and contributions towards managing digital transformation and (specific) IT innovations.

V.4 Conclusion

Summarizing the research papers presented in Chapter II, III, and IV, this doctoral thesis contributes to the existing literature in digital transformation and IT innovation management by providing new approaches for managing digital transformation from a holistic company perspective as well as for managing (specific) IT innovations. Although this doctoral thesis certainly can only answer some selected questions, it contributes to previous work in selected areas. Concluding, this doctoral thesis hopefully provides valuable theoretical and practical insights for some specific aspects of digital transformation and IT innovation management.

V.5 References

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