# New Approaches for Value-based IT Innovation Management

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***Please note:*** Tables and figures are consecutively numbered per chapter, and within Chapters II, III, and IV per section (each representing one research paper). References are provided at the end of each section and each research paper, respectively.

# Index of Research Papers

This doctoral thesis contains the following research papers:

**Research Paper P1:** Bürger O, Moser F (2019) Toward an Optimal Degree of Openness in IT Innovation Projects.

In: *R&D Management, 2019, 49(2), 239-251 (VHB-JOURQUAL 3: category B)*

**Research Paper P2:** Bürger O, Häckel B, Voit C (2020) Toward an Economically Optimal Team Design in IT-related Innovation Projects.

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

**Research Paper P3:** Bürger O, Häckel B, Moser F (2017) Towards an Optimal Investment Strategy Considering Fashionable IT Innovations – a Dynamic Optimisation Model.

In: *Journal of Decision Systems, 2017, 26(3), 229-255 (VHB-JOURQUAL 3: category B)*

**Research Paper P4:** Bürger O (2019) How to Structure a Company-wide Adoption of Big Data Analytics.

In: *Proceedings of the 14th Internationale Tagung Wirtschaftsinformatik (WI), Siegen, Germany, February 2019 (VHB-JOURQUAL 3: category C)*

**Research Paper P5:** Bitomsky L, Bürger O, Häckel B, Töppel J (2020) Value of Data Meets IT Security – Assessing IT Security Risks in Data-Driven Value Chains.

Published online in: *Electronic Markets, 2020, 1-17 (VHB-JOURQUAL 3: category B)*

# I Introduction[1]

Innovations are crucial for companies to sustain their competitiveness and profitability, especially in dynamic business environments (Patrakosol & Olson 2007). In the last years, information technology (IT) industry has provided a wide range of IT innovations that can be defined as innovations "[…] in the organizational application of digital computer and communications technologies (now commonly known as IT)" (Swanson 1994, p. 1072) by utilizing IT in new products and services, connecting organizations, and conducting business in new ways (Patrakosol & Olson 2007). Thus, IT and IT innovations are now considered as one of the most relevant value drivers from an economic and social perspective (Lucas Jr. et al. 2013) and an important factor for business success (Andal-Ancion et al. 2003; Barua et al. 2001; Ramirez et al. 2010; Schryen 2013). Moreover, the pervasive digitalization forces even low-tech companies to deal with IT innovations like big data analytics (BDA), internet of things (IoT), blockchain, or artificial intelligence (AI) and thus, reinforces the importance of IT innovations even in non-IT industries (Yoo et al. 2010). For example, automotive companies increasingly rely on IT innovations to shift their business models from carmakers to mobility service providers in order to keep pace with technology companies like Google, which is meanwhile active in the field of autonomous driving. Threatened by financial technology start-ups (also called FinTechs) that revolutionize how clients experience financial services (Mackenzie 2015), financial service providers offer new IT-based, data-driven services to meet the changing needs of their clients. Manufacturers also increasingly innovate with IT to improve the efficiency of production processes and to expand their traditional product offerings with new IT-based, data-driven services like predictive maintenance.

With regard to their ever-increasing importance in practice, it is not surprising that IT innovations gained high attention in research in recent years. To support companies in innovating with IT, prior research has investigated various phenomena related to IT innovations, mainly from two perspectives: 1) IT innovation creation, and 2) IT innovation adoption and diffusion (Patrakosol & Olson 2007). From the first perspective, studies focus on the development of IT innovations (e.g., King et al. 1994; Lyytinen & Rose 2003) and investigate, for example, how companies can enhance their innovativeness by improving their

[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 and III as well as the last Chapter IV are partly comprised of content taken from the research papers included in this thesis. To improve the readability of the text, I omit the standard labeling of these citations.

innovation processes to increase the quantity and quality of created IT innovations. From the second perspective, studies consider the organizational adoption and diffusion of already developed IT innovations (e.g., Fichman 2001; Swanson & Ramiller 2004), and investigate, for example, how companies can identify appropriate IT innovations and ensure their successful adoption and diffusion within the company. This doctoral thesis considers both perspectives and focuses on IT innovation creation and adoption. Thereby, both perspectives are closely intertwined because the goal of creating IT innovations is their adoption in-house or on the market. Vice versa, the adoption of already developed IT innovations can also aim at creating new IT innovations. For example, adopting BDA and AI allows for improving decision-making and efficiency of other internal processes, as well as for providing new data-based services and even business models (Buck & Eder 2018; Gimpel & Röglinger 2017). Thus, both creation and adoption of IT innovations are crucial for companies to survive in competitive environments (Patrakosol & Olson 2007; Schilling 2010; Yoo et al. 2010) since they enable companies to increase profitability, market share and future cash flows (Lu & Ramamurthy 2010; McAfee & Brynjolfsson 2008; Wang 2010).

Although creation and adoption of IT innovations can lead to manifold benefits for a company, they are also associated with various challenges. First, innovating with IT requires substantial financial and personnel resources, and bears a high uncertainty about their future development and associated cash flows (Fenn & Raskino 2008; Wang 2010). In particular, creation and adoption of IT innovations promise higher expected benefits due to the first mover advantage. However, they also bear the risk of developing IT innovations that do not (yet) meet the customer needs or the risk of investing in a losing technology. On the other hand, companies that refrain from creating and adopting IT innovations can be outpaced by competitors that make a breakthrough with one of their IT innovations and can be even driven out of the market. For example, Nokia, once a major player in the mobile phone market, missed the smartphone trend and was overtaken by rivals like Apple and Samsung. Second, the rapid technological progress accompanied by an increasing amount and variety of IT innovations as well as ever-shorter product life cycles, fast changes in customer behavior, and high market dynamics caused by globalization and new competitors force companies to continuously innovate with IT (Dreiling & Recker 2013; Leimeister et al. 2014; Nüesch et al. 2015; Priem et al. 2013). Thus, companies need to create a continuous flow of IT innovations and ensure a systematic adoption of IT innovations to sustain the company’s competitive advantage and to maximize its long-term value (Stratopoulos & Lim 2010).

To deal with these challenges, companies can incorporate the principles of a value-based management (VBM) in their IT innovation management. Based on the work of Copeland et al. (1990), Rappaport (1986), and Stewart (1991), VBM aims at sustainably increasing a company's firm value from a long-term perspective (Ittner & Larcker 2001; Koller et al. 2010). According to VBM, all business activities on all hierarchy levels should aim at maximizing the firm value. Therefore, companies should quantify the firm value on the aggregated level as well as the value contribution of individual assets, activities and decisions by taking into account their cash flow effects, their risks, and the time value of money (Buhl et al. 2011). Accordingly, a value-based IT innovation management aims at increasing a company's long-term firm value by making decisions and conducting activities related to innovation management based on their value contribution. Following the principles of VBM can enable companies to evaluate single IT innovations as well as IT innovation portfolios from an ex ante perspective to allocate the limited resources in such a way that risk and return potentials are balanced (Beccalli 2007; Kohli & Grover 2008; Lee et al. 2011; Melville et al. 2004; Schryen 2013). For example, companies can better decide on how to set up IT innovation projects (ITIPs) that aim at creating IT innovations by evaluating different project settings and selecting the one with the highest value contribution. Such evaluations also allow for a well-founded decision on which IT innovations to invest in by optimizing the investment strategy with regard to the associated risk and return potentials. Since adopting IT innovations can transform the company (e.g., organizational strategy and structure), as well as the way it interacts with its key partners and conducts its business (Patrakosol & Olson 2007), a value-based IT innovation management should also ensure that these activities meet the principles of VBM, especially its long-term orientation. For example, companies need to carefully plan and structure the adoption of IT innovations to ensure their successful diffusion within the company and to realize their value contribution (e.g., by improving efficiency of processes). Thereby, a well-planned and structured adoption may allow companies to avoid delays in the implementation phase by estimating the necessary resources and procuring them in time as well as by considering dependencies between individual activities early on. With regard to the transformation power of IT innovations, companies should also carefully analyze changes associated with their adoption. In particular, IT innovations can lead to considerable changes in the company's IT security risk landscape that should be identified early to prevent losses through IT security incidents. A profound IT security risk assessment may help companies to systematically identify the most important assets (the so called crown jewels) and to derive mitigation measures to protect them in an appropriate way in order to sustain the company's long-term firm value in the sense of VBM.

Following the two main perspectives within the research on IT innovations, this doctoral thesis investigates selected areas of a value-based IT innovation management and focuses on managing the creation of IT innovations (Chapter II) and managing the adoption of IT innovations (Chapter III).

*Managing the creation of IT innovations:* To satisfy their customers and compete within the market, companies need to provide a continuous flow of IT innovations (Rubera & Kirca 2017; Trkman et al. 2015). Thereby, the rapid technological progress and high market dynamics increasingly intensify the innovation race and force companies to ensure both, a high quantity and quality of created IT innovations. This leads, however, to a shortage of financial and personnel resources, and a higher risk of innovation failure due to a high time pressure. To approach this challenge, companies need to improve the effectivity and efficiency of innovation processes and leverage their value contribution in the sense of VBM. Thereby, innovation process 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). It is also often named as the "development funnel", as the mass of ideas at the beginning of the innovation process is filtered out during the process, so that in the end only a few IT innovations are commercialized (Goffin & Mitchell 2010, p. 17). An innovation process mainly consists of three phases: early phase (idea generation), mid-phase (development), and late phase (commercialization) (Frishammar & Ylinenpää 2007). The idea generation phase includes activities such as idea seeking and assessment, designing teams, and setup of innovation environment (e.g., software). The development phase typically consist of activities like core concept and design, testing and validation of prototypes, and marketing. In the commercialization phase, activities like market launch, customer service and sales are required (Frishammar & Ylinenpää 2007). Thereby, prior research states that measures that aim at improving innovation processes have the highest impact if they are conducted within their early and mid-phases (i.e., idea generation and development phase) (e.g., Christiansen 2000; Cobbenhagen 2000). For example, improvement measures in the idea generation phase may lead to better ideas and thus, to higher profits, whereas improvement measures in the development phase may allow for reducing the time-to-market and enable a faster market launch of IT innovations (Christiansen 2000; Enkel et al. 2005; Füller et al. 2006). Whereas prior research predominantly investigates the impact of various improvement measures at the organizational level, this doctoral thesis focuses on their impact at the project level. Since individual ITIPs can considerably differ related to their goal (e.g., developing a new app versus a blockchain-based business platform), the associated costs, risks, and benefits can also strongly vary. Consequently, companies also need to evaluate improvement measures at the project level to quantify the value contribution of individual ITIPs according to VBM.

As one possible improvement measure, companies can collaborate with external stakeholders, such as customers, suppliers, universities, or competitors (Chesbrough 2003, Enkel et al. 2009). Known as the open innovation (OI) paradigm, this well-known approach allows companies to enhance their innovativeness and make higher profits with more breakthrough ideas gained through knowledge exchange with external partners. Furthermore, applying OI can help companies to reduce costs through sharing resources and risks (Gassmann et al. 2010). However, applying OI can also lead to higher costs for communication and coordination, and additional risks such as knowledge depletion (Enkel et al. 2009). Moreover, it can be challenging and even fail (Enkel et al. 2005) due to organizational and cultural issues or missing know-how of how to find appropriate collaboration partners (Enkel et al. 2009; van de Vrande et al. 2009). Thus, companies need to decide to what extend and when to incorporate external stakeholders in their ITIPs in order to find an optimal degree of openness that balances the trade-off between benefits, costs and risks of applying OI. A further possible measure that companies can implement to improve their innovation processes aims at increasing the innovation team performance through an appropriate team design. To analyze the impact of team design on the associated output, the input-process-output (IPO) model of team performance is a widely used approach (Hackman 1987; Hülsheger et al. 2009; Kozlowski et al. 2015; McGrath 1964; West & Anderson 1996). Thereby, inputs refer to individual, team, and organizational context characteristics that influence the team output. Processes include characteristics that emerge from interactions among team members and also affect the team outcome. Outputs refer to the team results (e.g., quantity and quality of ideas or team member satisfaction) (Kozlowski et al. 2015; West & Anderson 1996). Whereas a suitable ITIP team design can increase the team performance (Hackman 1987; Hülsheger et al. 2009), this task can be challenging due to the opposing effects of different design parameters on the performance. For example, a high team diversity with respect to members' academic background or skills may lead to a higher probability of excellent ideas, but also increases communication and coordination costs due to communication problems (Garcia Martinez et al. 2017; Reagans & Zuckerman 2001). Thus, companies need to find an optimal team design that balances such opposing effects. Chapter II addresses these challenges and provides two novel approaches for a value-based, ex ante evaluation of ITIPs to support the optimal application of OI and team design from VBM's point of view.

*Managing the adoption of IT innovations:* To remain competitive, companies do not only have to provide a continuous flow of IT innovations, but also have to systematically adopt IT innovations in their own business activities. For example, IT innovations like BDA, AI, and blockchain are currently on the innovation agendas of many companies. However, the adoption of IT innovations may be challenging as it requires an ongoing investment in various IT innovations as well as a (partial) transformation of all levels of the enterprise architecture (e.g., IT infrastructure, processes and even business models). When deciding on which IT innovations to invest in, companies today face a high amount and variety of IT innovations offered by the market. For example, the current Gartner Hype Cycle highlights 35 "must-watch" IT innovations (e.g., smart dust, 4D Printing, or edge AI) out of the field of more than 2,000 topics that companies should bring on their innovation agenda (Gartner 2018). Moreover, as illustrated by the Gartner Hype Cycle, IT innovations undergo a life cycle and thus, have different maturity (Fenn & Raskino 2008). An IT innovation's life cycle starts with a *technology trigger*, in which only a small group of early innovators is engaged. Accompanied by excessive publicity that often leads to over-enthusiasm and bandwagon behavior, an IT innovation moves on to the next phase where the hype usually reaches a *peak of inflated expectations* before it fades away in a *trough of disillusionment*. Thus, only few IT innovations reach a *slope of enlightenment* and finally, a *plateau of productivity* (Fenn & Raskino 2008) with their successful institutionalization and broad adoption by most of the companies. Based on this life cycle, IT innovations can be distinguished in fashionable and mature IT innovations related to their maturity (Fridgen & Moser 2013; Häckel et al. 2013a; Häckel et al. 2013b; Häckel et al. 2016; Häckel et al. 2017; Moser 2011). Thereby, fashionable IT innovations are IT innovations that are in an evolutionary phase between technology trigger and trough of disillusionment (Fenn & Raskino 2008; Wang 2010) and are accompanied by a hype. In contrast, mature IT innovations have already reached an evolution between the slope of enlightenment and the plateau of productivity (Fenn & Raskino 2008) or have already been adopted by a significant share of the market (Rogers 2003). Due to their different maturity, IT innovations are associated with different benefits and risks (see e.g., Häckel et al. 2017; Moser 2011). Whereas fashionable IT innovations can lead to high returns that can be realized through first mover advantages but also bear high risks of a failure, mature IT innovations bear lower risks but also imply lower expected returns, since the first mover advantages cannot be realized anymore (Swanson 1994; Swanson & Ramiller 2004). Thus, companies need to decide whether, when and to which extend to invest in IT innovations with different maturity in order to optimize their investment strategy with regard to risk and return perspectives following the principles of VBM. Prior research has already addressed this challenge from various perspectives while setting different focus of investigation and using different methodology. For example, Moser (2011) has analyzed fashionable IT innovations regarding their idiosyncrasies and thus, risk and return potentials. Based on analysis of Moser (2011) and portfolio selection theory of Markowitz (1952), Fridgen and Moser (2013) have investigated how engaging in fashionable IT innovations can help companies to optimize their IT innovation portfolio. Moreover, there exist several studies that provide approaches for optimizing the investment strategy for IT innovations with different maturity based on dynamic optimization models. Whereas the basic model setting is rather similar in these studies (e.g., risk neutral decision-maker, decision tree approach, innovations with different maturity), the main focus of the respective investigation strongly differs. For example, Häckel et al. (2013b) analyze the potential error of so-called fixed IT innovation investment strategies where the budget allocation does not change over time by evaluating the deviations from an optimal investment strategy and the resulting over- or underinvesting in fashionable IT innovations. Häckel et al. (2017) focus on the influence of organizational learning on the optimal IT innovation investment strategy and the resulting adjustment of budget allocation over time from a long-term perspective. Häckel et al. (2013a) also consider organizational learning and analyze the potential error of fixed IT innovation investment strategies. Similarly, Häckel et al. (2016) focus on organizational learning, but evaluate different IT innovation investment strategies from an ex ante and ex post perspective. Whereas all these studies already provide approaches for determining the optimal investment strategy for IT innovations with different maturity, they mainly focus on analyzing organizational learning or evaluating deviations from an optimal investment strategy and are based on an n-period setting in order to investigate the long-term effects of organizational learning. Thus, these studies do not consider further impact factors that may drive the strategic allocation of a company's IT innovation budget (e.g., company's innovator profile, IT innovation's success probability etc.). Companies, however, need to incorporate these impact factors in their decision calculus for a well-founded decision-making.

As mentioned above, BDA is an illustrative example of IT innovations that have been very hyped in recent years and are still very topical today. Since insight-driven organizations (IDOs) are predicted to capture revenue of USD 1.2 trillion from their (less-informed) competitors by 2020 (McCormick et al. 2016), companies increasingly adopt BDA to become

IDOs that use BDA as a competitive differentiator. However, to develop toward an IDO, a company needs to adopt BDA across the whole company and anchor it in nearly all business activities instead of utilizing it in only a single application, for example. Due to its high transformation potential, a company-wide BDA adoption is challenging as it needs high investment amounts, involves different stakeholder groups, and affects various levels of the enterprise architecture (Baesens et al. 2016; Röglinger et al. 2016). Thus, companies need to carefully plan and structure the adoption of BDA to derive, coordinate, and prioritize the individual activities, taking into account the manifold dependencies in terms of content and time. By doing so, they can ensure the value contribution of adopting BDA in general as well as of all activities required within the implementation phase in the sense of VBM. Moreover, companies should carefully evaluate the changes that may arise through the adoption of IT innovations to ensure the value contribution of the affected activities and assets. For example, the company-wide adoption of BDA leads to an increasing strategic importance of data and consequently, to higher risks of data breaches. Especially manufacturing companies that shift from a product-centric to a customer-centric, highly data-driven value creation face considerable changes in their IT security risk landscape. To protect their new data-based crown jewels in an appropriate way, companies need to carefully assess IT security risks arising through the shift to a data-driven value creation. Chapter III addresses these challenges and provides novel approaches to evaluate investments in IT innovations with different maturity, to structure the company-wide adoption of BDA, and to assess the associated IT security risks arising through the shift to a data-driven value creation as an example of one major challenge associated with adopting IT innovations.

In sum, this doctoral thesis addresses the need for managing the creation and adoption of IT innovations based on the principles of VBM to sustainably increase a company’s firm value from a long-term perspective in dynamic market environments. The following Section I.1 illustrates the objectives and structure of the doctoral thesis. The subsequent Section I.2 embeds the corresponding research papers in the research context and highlights the fundamental research questions.

## I.1 Thesis Objectives and Structure

The main objective of this doctoral thesis is to contribute to the field of (IT) innovation management by providing new approaches that support the management of the creation and adoption of IT innovations following the principles of VBM. 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 doctoral thesis' motivation, objectives, and the structure |
| Objective I.2: | Embedding the included research papers into the context of the doctoral thesis and formulating the key research questions |
| **II Managing the Creation of IT Innovations (Research Papers 1 and 2)** | |
| Improving the value contribution of ITIPs by providing value-based, ex ante evaluation approaches that allow for optimizing … | |
| Objective II.1: | … their degree of openness to balance the trade-off between benefits, costs and risks of applying OI |
| Objective II.2: | … their team design to balance the opposing effects of different design parameters on the performance |
| **III Managing the Adoption of IT Innovations (Research Papers 3 – 5)** | |
| Objective III.1: | Improving the investment strategy by developing a value-based, ex ante evaluation approach to optimally allocate a strategic IT innovation budget to IT innovations with different maturity |
| Objective III.2: | Assisting companies in planning and structuring a company-wide adoption of BDA by designing a roadmapping-based method |
| Objective III.3: | Enabling the assessment of IT security risks arising through the shift to a data-driven value creation by providing a modeling approach to analyze data types in terms of value contribution and affiliated IT security risks |
| **IV Results, Future Research, and Conclusion** | |
| Objective IV.1: | Presenting the doctoral thesis' key findings |
| Objective IV.2: | Identifying and highlighting areas for future research |

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

## I.2 Research Context and Research Questions

This section aims at motivating the research questions of research papers P1 to P5 included in Chapters II and III. As outlined above, this doctoral thesis focuses on selected areas of managing the creation of IT innovations (Chapter II) and managing the adoption of IT innovations (Chapter III), and does not consider IT innovation diffusion.

In Chapter II, research papers P1 and P2 address the need for managing the creation of IT innovations by following the principles of VBM. Therefore, they focus on improvement of ITIPs' value contribution and investigate how companies can evaluate their ITIPs from an ex ante perspective to optimize the degree of openness when applying OI (P1), as well as to optimize the team design (P2). In Chapter III, research papers P3, P4, and P5 deal with managing the adoption of IT innovations. Thereby, P3 focuses on improvement of the investment strategy and investigates how to allocate a strategic IT innovation budget to IT innovations with different maturity to balance their risk and return potentials. Based on the example of BDA, P4 addresses the need for carefully planning and structuring the adoption of IT innovations to ensure the realization of their value contribution in the sense of VBM, whereas P5 points out the importance of evaluating the changes arising through this adoption, for example by assessing the associated IT security risks. Figure I.2-1 provides an overview of the papers included in this doctoral thesis.

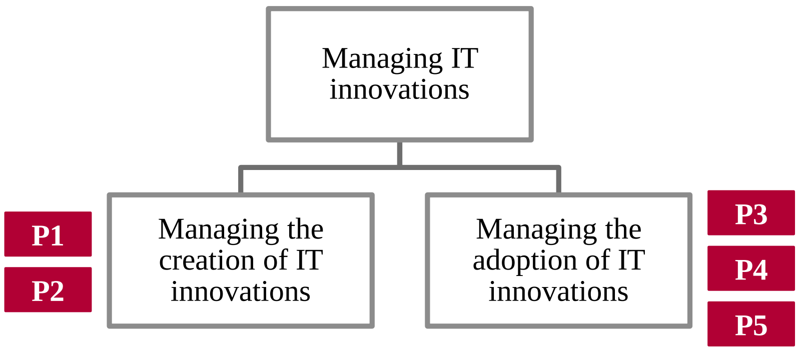


**Figure I.2-1:** Research papers included in the doctoral thesis

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: Managing the Creation of IT Innovations

Digitalization forces even low-tech companies to include IT innovations in their innovation management to sustain their competitiveness. However, the creation of IT innovations can be challenging for both IT and non-IT companies due to high investments needed combined with a high uncertainty about future cash flows. To remain competitive, companies need to improve their innovation processes, for example, by applying OI in their ITIPs or by increasing the team performance through an appropriate team design. Since such improvement measures affect the value contribution of ITIPs differently, companies should carefully evaluate their implementation at the project level. This chapter addresses this issue and provides new approaches for a value-based, ex ante evaluation of ITIPs with regard to applying OI and designing the ITIP team that may assist companies in balancing the associated trade-offs, as well as allocating the limited resources in a way that supports the principles of VBM.

***Research Paper P1:*** *"Toward an Optimal Degree of Openness in IT Innovation Projects"*

P1 focuses on creation of IT innovations in collaboration with external partners and provides a new approach for an ex ante financial evaluation of ITIPs related to the application of OI. Introduced by Chesbrough (2003), the OI paradigm has gained high attention in research and practice during the last years (Schroll & Mild 2012). Whereas applying OI helps companies to generate more breakthrough ideas through knowledge exchange with external partners, as well as to share resources and risks with them (Gassmann et al. 2010), it also leads to additional costs (e.g., communication costs) and risks (e.g., knowledge depletion) (Enkel et al. 2009). Thus, companies need to decide to which extend to involve external partners in their ITIPs in order to find an optimal degree of openness that balances this trade-off. Moreover, the application of OI in the early and mid-phases of an innovation process (i.e., idea generation and development phase) promises greater benefits due to higher chances of generating breakthrough ideas (Enkel et al. 2005; Huizingh 2011), but also bears higher risks of knowledge depletion. Thus, companies also have to decide when to involve the external partners in their ITIPs. To support companies in making these decisions, P1 develops a model for determining the optimal degree of openness in different phases of an ITIP, considering the associated costs, risks, and benefits. Since applying OI is challenging and can even fail (Enkel et al. 2005), P1 further examines the influence of a company's ability to manage OI and the probability of success in OI application on the optimal degree of openness and, consequently, on the value contribution of the ITIP. In sum, P1 addresses Objective II.1 from Table I.1-1 by answering the following research questions:

- What is the optimal degree of openness in different phases of an ITIP, relative to the associated costs, risks, and benefits?
- How does a company's ability to manage OI and the probability of success in OI application affect the optimal degree of openness?

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

P2 also focuses on ITIPs that aim at creating IT innovations and provides a novel approach for their ex ante financial evaluation to improve the value contribution by optimizing the team design. According to the input-process-output (IPO) model, an appropriate team design can positively influence the team performance. However, different team design factors (e.g., team size or academic background diversity) have opposing effects on the team performance. For example, a high geographic dispersion may increase the team performance due to a more comprehensive understanding of global markets (Boutellier et al. 1998; Gluesing & Gibson 2004). However, at the same time, it also can negatively affect the team performance due to cultural differences and communication problems (Hinds et al. 2011; Kozlowski et al. 2015). Thus, companies can benefit from finding an optimal team design to balance the involved trade-offs. Since different team design factors also considerably affect the anticipated benefits and costs of an ITIP (Garcia Martinez et al. 2017; Hoisl et al. 2017; Horwitz & Horwitz 2007; Hülsheger et al. 2009), companies need to take into account these effects when designing an ITIP team. To support companies in approaching these challenges, P2 develops a model for determining the optimal team design for an ITIP by considering the associated benefits and costs. Furthermore, P2 analyzes how selected company- and employee-specific characteristics influence the project success to assist companies in identifying the most critical team design parameters and simulating various scenarios. In sum, P2 addresses Objective II.2 from Table I.1-1 by stating the following research questions:

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

### I.2.2 Chapter III: Managing the Adoption of IT Innovations

Driven by digitalization, companies also face the need to systematically adopt IT innovations in their business activities. Since IT innovations have a different maturity related to their life cycle and thus, are associated with different benefits and risks, companies should mindfully evaluate investments in IT innovations with different maturity to balance their investment strategy with regard to the associated risk and return potentials. Moreover, a high transformation potential of IT innovations requires a careful plan and structure of their adoption to ensure their value contribution and a successful diffusion in the company later. Finally, adopting IT innovations can lead to changes at different levels of the enterprise architecture, such as changes in the company's security risk landscape that should be carefully analyzed to avoid losses or inefficiencies and to ensure the long-term company success. Thus, this chapter addresses these challenges and provides novel approaches that may support companies in overcoming the outlined hurdles.

***Research Paper P3:*** *"Towards an Optimal Investment Strategy Considering Fashionable IT Innovations – a Dynamic Optimisation Model"*

P3 focuses on situations, in which companies need to decide which IT innovations to invest in. The dynamic development of IT (innovations), as well as increasing competition and changing customer expectations increasingly force companies to invest in emerging, but immature IT innovations (Lu & Ramamurthy 2010; Swanson & Ramiller 2004) to remain competitive. In contrast to mature IT innovations that have already been adopted by a significant share of the market (Rogers 2003), emerging IT innovations (also called fashionable IT innovations) are in an early development phase and are accompanied by a hype through a fashion-setting network (Fenn & Raskino 2008; Moser 2011; Wang 2010). Whereas investing in fashionable IT innovations promises higher benefits due to first mover advantages and higher market shares in the case of their institutionalization, it also bears the risk of investing in a losing technology (Fridgen & Moser 2013; Häckel et al. 2013a; Häckel et al. 2013b; Häckel et al. 2016; Häckel et al. 2017; Moser 2011). Especially for small businesses that have invested a high amount in fashionable IT innovations, their non-institutionalization can even lead to bankruptcy (Stratopoulos & Lim 2010). In contrast, investing in mature IT innovations is less risky due to their advanced evolution, but also less beneficial as companies cannot realize first mover advantages anymore (see e.g., Häckel et al. 2017; Moser 2011). Thus, companies need to decide whether, when and to which extend to invest in fashionable and mature innovations to balance their investment strategy with regard to the associated risk and return potentials of these IT innovations. To support companies in approaching this problem, P3 refers to previous work of Fridgen & Moser (2013), Häckel et al. (2013a), Häckel et al. (2013b), Häckel et al. (2016), Häckel et al. (2017), and Moser (2011) and develops a dynamic optimization model for determining the optimal strategic allocation of an IT innovation budget to mature and fashionable IT innovations. Whereas P3's basic model setting is similar to approaches provided by Häckel et al. (2013a), Häckel et al. (2013b), Häckel et al. (2016), and Häckel et al. (2017), the focus of its analysis is different as it examines how company- and technology-specific factors influence the optimal allocation of a company's strategic IT innovation budget. In accordance with Objective III.1 from Table I.1-1, P3 addresses the following research questions:

- What is a strategic IT innovation budget's optimal allocation to mature and fashionable IT innovations?
- How do company- and technology-specific factors influence the strategic IT innovation budget's allocation to mature and fashionable IT innovation investments?

***Research Paper P4:*** *"How to Structure a Company-wide Adoption of Big Data Analytics"*

P4 considers a situation in which a company aims to adopt BDA across the whole company to gain value from data. In general, companies adopt BDA to establish competitive advantage by delivering value and improving efficiency (Müller et al. 2016; Wamba et al. 2017). Thereby, a company-wide adoption of BDA and using it as a competitive differentiator enable companies to become IDOs that tend to have a better performance with regard to financial and operational results (LaValle et al. 2011; McAfee et al. 2012). However, the company-wide adoption of BDA may be challenging due to its high transformation potential as well as time and cost intensity (Baesens et al. 2016; Röglinger et al. 2016). Thus, to ensure the value contribution of all activities required for a company-wide adoption of BDA, companies need to handle this complexity and carefully plan and structure the adoption. To support companies in this effort, P4 develops and evaluates a new method for structuring the company-wide adoption of BDA in a concerted research effort with a German bank. The case-study bank is a typical and representative example (Yin 2014), because changing client behavior (Iansiti & Lakhani 2017) and new market players like FinTechs (Alt et al. 2018) force financial service providers to innovate their interactions with clients and current value delivery (Mackenzie 2015). However, although financial service providers have a large volume of client data, they are not yet able to generate value from it. Based on the roadmapping approach, the new method allows for deriving, coordinating and prioritizing the individual adoption measures as well as taking into account the dependencies in terms of content and time. In sum, P4 addresses Objective III.2 from Table I.1-1 by stating the following research question:

- How can developing a roadmap assist in structuring the company-wide adoption of BDA?

***Research Paper P5:*** *"Value of Data Meets IT Security – Assessing IT Security Risks in Data-Driven Value Chains"*

Since IT innovations can transform the entire company, as well as the way it conducts its business and interacts with its partners (Patrakosol & Olson 2007), companies should also carefully analyze the changes that may arise through their adoption. As outlined by P4, adopting BDA across the company, can, for example, lead to changes within technology and data (e.g., new BDA tools or data policies), as well as processes (e.g., more automated and data-supported processes). Since an increasing integration of IT in business activities may in particular lead to changes in the company's IT security risk landscape, companies need to analyze these changes in order to prevent IT security issues. P5 deals with the changes in a manufacturing company's security risk landscape arising through the shift to a data-driven value creation. For example, the increasing strategic importance of data attracts adversaries and leads to a higher number of attacks. Integrating data into products and services, as well as sharing it with external partners and in-house increases the attack surface. Finally, the increasing dependency of value creation on data can lead to a considerable damage when data breaches occur. Consequently, companies need to evaluate the value contribution of their data and to measure the associated risks to protect their data-based crown jewels in an appropriate way. Such evaluation could also serve as a basis for deriving mitigation measures later. Therefore, the objective of P5 is to enable the assessment of IT security risks arising through the shift to a data-driven value creation by providing a modeling approach to analyze data types in terms of value contribution and affiliated IT security risks (cf., Objective III.3 from Table I.1-1).

### I.2.3 Chapter IV: 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, Chapters II and III present the research papers. Subsequently, Chapter IV provides the key findings and highlights areas for future research in the fields of managing the creation and adoption of IT innovations.

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# II Managing the Creation of IT Innovations

This chapter deals with managing the creation of IT innovations. To approach the high complexity and uncertainty of IT innovations as well as the challenge of limited personnel and financial resources, companies are looking for ways to improve their innovation processes by increasing the value contribution of their ITIPs through various measures. Since these measures affect the associated ITIPs differently, an ex ante financial evaluation of ITIPs can help companies to approach the involved trade-offs and to allocate the limited resources in a way that supports the principles of VBM (Fridgen & Moser 2013; Häckel et al. 2017). Hence, this chapter includes two research papers that provide new approaches for a value-based, ex ante evaluation of ITIPs with regard to conducting two exemplary measures (applying OI and designing the ITIP team) to improve the management of IT innovation creation.

The first research paper P1 "*Toward an Optimal Degree of Openness in IT Innovation Projects*" in Chapter II.1 provides a novel approach for an ex ante financial evaluation of ITIPs related to the application of OI. P1 develops a theoretical model for determining the optimal degree of openness in ITIPs that is evaluated by means of a simulation-based approach and a real-life case of a bank group. P1 examines relevant causal relationships by analyzing the influence of a company's ability to manage OI and the probability of success in OI application on the theoretical optimum.

The second research paper P2 "*Toward an Economically Optimal Team Design in IT-related Innovation Projects*" in Chapter II.2 provides an approach for an ex ante financial evaluation of ITIPs related to the team design. Similar to P1, P2 develops a model for determining the optimal team design for an ITIP that is evaluated by means of a simulation-based approach and interviews with industry experts. P2 examines relevant causal relationships by analyzing the influence of selected team design factors on the theoretical optimum and illustrates the model's applicability in a real-life case of a start-up in the financial services industry.

## II.1 Research Paper 1: "Toward an Optimal Degree of Openness in IT Innovation Projects"


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**Abstract:**

*In spite of substantial interest in open innovation (OI), both research and practice lack methods that support companies in managing their IT innovation projects (ITIPs) relative to OI. We contribute to the closure of this gap by providing an approach for an ex ante financial evaluation of OI application, which involves developing a theoretical model that determines the optimal degree of openness in ITIPs. Based on our model, we examine relevant causal relationships by analyzing the influence of a company's ability to manage OI and the probability of success in OI application on the theoretical optimum. We find that the optimal openness level is linked with the company's ability to manage OI, which can incorporate organizational, cultural, and technological maturity. To increase the value contribution of OI, companies should focus on a steady improvement in managing OI. The results provide both an indicator for practical decision-making and a starting point for future research.*


[1] The affiliation of Florian Moser has been updated because Mr. Moser changed his job after the publication of the paper.

### II.1.1 Introduction

In a digital economy, companies regularly address recent IT trends, such as the Internet of Things (IoT) or Big Data, and implement IT-based innovations (e.g., smart cars or mobile devices) in their innovation management to sustain their competitiveness. However, innovating with IT is challenging for both IT and non-IT companies, as new technologies require substantial effort in their experimentation to understand their applicability, risks, and benefits. Companies approach this challenge by using open innovation (OI) for capturing new ideas and IT knowledge, and for sharing resources and risks in their IT innovation projects (ITIPs).

A well-known approach, OI allows companies to enhance their innovativeness through knowledge exchange with external partners. Meanwhile, 78% of large European and US firms reported that they practice OI (Chesbrough and Brunswicker, 2014). The application of OI is associated with various benefits, such as higher profits and innovation rates, and reduced costs through sharing risks and resources (Gassmann et al., 2010). However, applying OI leads to higher costs for communication and coordination, and such risks as knowledge depletion (Enkel et al., 2009). Thus, companies benefit from finding an optimal degree of openness to balance this trade-off, and can measure it differently, for example, through the breadth and depth of external search channels (Laursen and Salter, 2006). Further, the impact of applying OI varies during the innovation process. As OI application in the early phases of an innovation process is considered more beneficial due to the greater potential to generate breakthrough ideas (Enkel et al., 2005) or save costs (Huizingh, 2011), companies must also decide when they should apply OI.

As ITIPs can differ (e.g., incremental ITIPs may include new apps, versus radical ITIPs, which may include a blockchain-based business platform), they must mindfully analyze OI application in different project phases relative to the associated costs, risks, and benefits. However, prior research on the degree of openness has focused on the organizational level, and has not considered applying OI at the project level. Thus, we derive our first research question:

RQ1: *What is the optimal degree of openness in different phases of an ITIP, relative to the associated costs, risks, and benefits?*

Although OI is widely applied in practice, failures still occur in opening an innovation process (Enkel et al., 2005). This raises our second research question:

RQ2: *How does a company's ability to manage OI and the probability of success in OI application affect the optimal degree of openness?*

As previous research focuses on identifying the optimal degree of openness at the organizational level, and from an *ex post* perspective, methods that support *ex ante* financial evaluations of OI application in ITIPs are virtually non-existent. We aim to contribute to the closure of this research gap, and to assist companies in becoming more advanced in evaluating their activities around ITIPs, by offering an approach that supports mindful decisions regarding when, and to what extent, to apply OI in ITIPs.

Therefore, we apply a simulation-based approach by following Meredith et al. (1989) and Davis et al. (2007).We develop a formal-deductive mathematical model to determine the optimal degree of openness in ITIPs, and analyze this relative to the optimum and major impact factors.

The remainder of this paper is organized as follows: First, we provide a brief overview of relevant literature in Section 2. Section 3 develops our model, which is analyzed in Section 4. We conclude by discussing the implications in Section 5 and limitations and outlook in Section 6.

### II.1.2 Related Literature

Literature defines OI as the use of inbound and outbound knowledge flows to accelerate internal innovation and expand markets to externally use innovation, respectively (Chesbrough et al., 2006). Our work focuses on inbound OI, which aims to enrich a company's competences through collaboration with external stakeholders (Enkel et al., 2009).

Regarding OI's influence on innovation performance, prior research considers various benefits and possible associated risks (e.g., Chesbrough, 2003; Enkel et al., 2005; Laursen and Salter, 2006; Patrakosol and Olson, 2007). Thereby, prior research states that openness generally has a positive impact on innovation performance, but too much openness can be negative, due to an excess of costs and risks (Laursen and Salter, 2006; Patrakosol and Olson, 2007). The optimal degree of openness is exemplarily represented as a continuum, ranging from 'closed' to OI. This can be defined either through the breadth and depth of external search channels (Laursen and Salter, 2006), or the number and type of stakeholders involved and the number and type of opened innovation process phases (Lazzarotti and Manzini, 2009).

Prior research intensively investigated how companies can successfully apply OI, as applying OI is challenging. For example, Durst, S. and Ståhle (2013) provide an overview of the critical success factors in applying OI (e.g., resources or culture). Others investigated how companies can develop their OI management abilities based on the success factors. For example, Hosseini et al. (2017) developed an OI capability framework, which includes capability areas grouped along factors that should be considered when applying OI, from strategic alignment to culture.

Moreover, OI can reduce costs or outcome uncertainty for ITIPs, often characterized by high investment and uncertain outcomes, by resource-sharing with collaboration partners and using their IT knowledge, which they are specialized in. Especially companies that are not involved in the latest developments or do not afford an own R&D department or IT Lab can benefit from it. However, IT innovations' potential to disrupt entire business models and industries increases their strategic importance. For example, IT innovations are crucial for automotive companies to shift their business models from carmakers to mobility service providers. Meanwhile, financial service providers compete with IT-based, data-driven services, or 'FinTechs'. Manufacturers innovate with IT to digitalize their factories via IoT. Thus, OI can also lead to a considerable loss in market shares for ITIPs with high strategic importance through knowledge depletion, inappropriate partner selection, or failing coordination. As nearly every company must challenge its business model and compete with IT innovation, knowledge loss, in particular, can lead to a considerable disadvantage by losing first-mover benefits in a highly competitive market. To handle this trade-off, ITIP management requires a well-founded ex ante financial evaluation of applying OI in ITIPs.

Prior research focuses on an *ex post* analysis of OI at the organizational level through empirical research. In contrast, formal-deductive and mathematical research on the *ex ante* financial evaluation of OI is underrepresented, and especially at the project level. A rare exception is the work of Baldwin and von Hippel (2011), who analyze three innovation models by assessing their economic viability. The research gap is even broader within IT innovation research, and especially regarding IT innovation creation (Patrakosol and Olson, 2007) and the *ex ante* evaluation of opening ITIPs. Thus far, Mette et al. (2013) provide the only quantitative, formal model to determine optimal investment amounts in OI activities for mobile services.

We contribute to the closure of this research gap by developing a theoretical optimization model, which aims to determine the optimal degree of openness in ITIPs, thus allowing an *ex ante* financial evaluation based on associated future cash flows. We are aware that not all idiosyncrasies and soft benefits, such as a company's reputation as an innovator, can be explicitly measured through cash flows. However, such factors can be incorporated within a second step (Irani and Love, 2002); despite some limitations, financial 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.

### II.1.3 Determining the Optimal Degree of Openness in ITIPs

#### *II.1.3.1 Research methodology*

We answer our stated research questions by applying mathematical simulation as a type of analytical modeling and a common research method (Meredith et al., 1989). We further follow Meredith et al. (1989) and Davis et al. (2007) due to missing empirical data in our domain, and apply a simulation-based approach to analyze causal relationships between the optimal degree of openness and the considered model parameters. Thus, we consider a real-life case, in which a banking group decides to apply OI in an ITIP given a sample project setting. We use this case to conduct our first analyses regarding the optimal degree of openness and achieved net present value (NPV). We subsequently broaden our study by conducting sensitivity analyses and a Monte Carlo simulation to more generically examine causal relationships. This is because simulation methods are a legitimate mechanisms in analyzing complex interrelationships (Meredith et al., 1989) and developing knowledge and theory (Davis et al., 2007). Despite some limitations, our work can set the foundation for future empirical research to strengthen the external validity of both our analysis and the gained insight (Meredith et al., 1989).We address our approach's limitations in detail and provide directions for future research in Sections 5 and 6.

#### *II.1.3.2 The Model*

We consider a company that evaluates an ITIP *ex ante* ($t = 0$), based on the future cash flows discounted to their NPV. The ITIP can be divided into several subprojects, which can be conducted either in-house (closed innovation, or 'CI') or with external stakeholders (OI). Thus, we do not differentiate between innovation types, stakeholder groups, and OI instruments. We begin with the assumptions for a CI process, and extend these through the idiosyncrasies of OI.

#### II.1.3.2.1. Assumptions for a CI Process

Assumption 1: *The company's innovation process consists of three phases: idea generation, development, and commercialization*.

Assumption 2: *The company is risk-neutral, and five cash flow types exist within the innovation process. Cash outflows are assumed as deterministic, as they are considerably easier to estimate than uncertain cash inflows. Cash inflows incorporate the uncertainty of the success in applying OI. The company discounts cash flows at a company-wide discount rate for ITIPs* $r$, *with* $0 < r \leq 1$.

Assumption 2.1: *The idea generation phase includes cash outflows for project initiation costs* $I_0 \geq 0$ *(e.g., expenditures for project laboratories, collaboration platforms, IT hosting, and test environments)*.

Assumption 2.2: *The idea generation phase includes cash outflows for costs of coordination* $CC_I \geq 0$ *(e.g., expenditures for team organization, consulting work, communication, and monitoring)*.

Assumption 2.3: *Analogous to* $CC_I$, *the development phase includes cash outflows for coordination costs* $CC_D \geq 0$.

Assumption 2.4: *The development phase includes cash outflows for marketing costs* $M \geq 0$ *(e.g., artwork, content creation, and search engine optimization). Although the commercialization phase also includes marketing costs, the vast majority are already realized before market launch (e.g., for the pre-announcement). Thus, we deliberately neglect the lower marketing costs in the commercialization phase to reduce the model's complexity*.

Assumption 2.5: *The commercialization phase includes cash inflows from sales. Although the cash inflows typically depend on a new product's life cycle, they are assumed as constant, and are modeled as a perpetuity* $S \geq 0$ *to reduce complexity*.

We then consider the cash flows $I_0$, $CC_I$. $CC_D$, $M$, and $S$ as reference points, and examine the impact of applying OI.

### II.1.3.2.2. Assumptions for an OI Process

As applying OI is considered more beneficial in the early phases of the innovation process (Enkel et al., 2005), we assume that the company opens its innovation process in the idea generation and development phases.

We follow recent literature to consider the degree of openness as a point between CI and OI, whereby some parts of the ITIP open and others close (Dahlander and Gann, 2010). At the project level, for example, the degree of openness can indicate how many subprojects are conducted with external stakeholders; or how many external beta-testers, influencers, or pre-studies, such as design-thinking activities, are involved or conducted. The possible number of subprojects varies based upon the type of ITIP or the company's business model. Recent technology-driven trends, such as fast-shared infrastructures, standardized application programing interfaces (APIs), agile development with quick sprints and prototyping, design thinking, or crowd-based development and testing allow for a higher divisibility among ITIPs (Enkel et al., 2009; Dahlander and Gann, 2010). Thus, the degree of openness can hypothetically have any value between 0% and 100%, as stated in the following assumption:

Assumption 3: *For each ITIP, a company can choose the degree of openness $\lambda_i$ with $0 \leq \lambda_i \leq 1$ for $i = 1, 2$, whereby $i$ depicts the respective phase of the innovation process. Thus, $\lambda_1$ depicts the degree of openness in the idea generation phase, and $\lambda_2$ the degree of openness in the development phase. While $\lambda_i = 0$ implies a completely closed ITIP, $\lambda_i = 1$ means that the ITIP is completely open in phase $i$.*

Applying OI in the early phases of the innovation process is more beneficial, but also can lead to higher costs (due to the high effort in evaluating a mass of new ideas) or a higher risk of knowledge depletion through deeper insights into the entire innovation process. Therefore, we further assume that $\lambda_1$ has a stronger impact on cash flows than $\lambda_2$.Moreover, we assume that applying OI in the early phases of the innovation process impacts the cash flows in the later phases; thus, $\lambda_1$ impacts $M$ and $S$, and $\lambda_2$ impacts S. For example, $\lambda_1$ implies lower $M$ (e.g., when external stakeholders promote a co-developed product) and higher $S$ due to the greater potential to generate breakthroughs. As applying OI impacts cash flows differently (Almirall and Casadesus-Masanell, 2010; Dahlander and Gann, 2010), we model in the following assumption the possible relationships between the degree of openness $\lambda_i$ in $i = 1, 2$ and the cash flows $I_0$, $CC_I$. $CC_D$, $M$, and $S$.

Assumption 4.1: *Project initiation costs* $I_0(\lambda_1)$ *decrease with greater openness due to economies of scale and the pooling of complementary competencies by sharing costs, and reducing a possible lack of capabilities and financing (Gassmann, 2006). Depending on the ITIP setting and collaboration partner involved, applying OI can lead to increasing* $I_0(\lambda_1)$ *in a very few cases (e.g., establishing a complex innovation platform). However, we assume that* $I_0(\lambda_1)$ *decreases due to the dominance of the OI sharing effect*.

Assumption 4.2: *The costs of coordination* $CC_I(\lambda_1)$ *increase with greater openness. Finding the right external stakeholders or ideas can be difficult and expensive due to the additional costs of negotiating law contracts or conducting idea assessments. Further, organization and communication expenditures increase as a result of the greater difficulty in motivating and coordinating dispersed teams (Gassmann et al., 2010) negotiating cultural differences (Dahlander and Gann, 2010), and managing shared IT platforms (Andresson et al., 2008). A possible lack of trust increases monitoring expenditures (Gassmann, 2006)*.

Assumption 4.3: *Analogous to* $CC_I(\lambda_1)$, *the costs of coordination* $CC_D(\lambda_2)$ *increase with greater openness*.

Assumption 4.4: *Marketing costs* $M(\lambda_1, \lambda_2)$ *decrease with greater openness, as users can promote IT innovation before a market launch; collaborating with competitors can help to establish powerful standards or share marketing costs (McGrath, 1997)*.

Assumption 4.5: *The cash inflows from sales* $S(\lambda_1, \lambda_2)$ *behave differently with greater openness. A successful OI application can enable higher* $S^u(\lambda_1, \lambda_2) \geq 0$ *(upside scenario u). A failed OI application can lead to knowledge depletion and lower* $S^d(\lambda_1, \lambda_2) \geq 0$ *(downside scenario d), whereby* $S^d(\lambda_1, \lambda_2) \leq S^u(\lambda_1, \lambda_2)$. *We assume that every IT innovation brings at least low or no cash inflows, even in a worst-case scenario. For example, an IT innovation may not be broadly commercialized due to incorrect market expectations or a similar product commercialized earlier by a competitor, or a failed OI application. Thus, we do not model the negative cash inflows from sales as we assume that from an ex ante perspective, no losses from sales are expected, as in this case the company would not launch the product. However, the initial investment costs still exist, which might lead to an overall negative NPV. We model the possible uncertain outcomes by considering the probability of success in OI application p* *with* $0 < p < 1$. *Thus, applying OI either increases* $S^u(\lambda_1, \lambda_2)$ *with the probability* $p$ *or decreases* $S^d(\lambda_1, \lambda_2)$, *with the probability* $(1 - p)$, *and leads to an expected value of* $S(\lambda_1, \lambda_2) \geq 0$.

Assumption 5: *The company's ability to manage OI is measured by the ability factor* $v$, *with* $0 < v < 1$, *where a lower* $v$ *implies a lower ability to manage OI, and vice versa. Thereby,* $v$ *can be influenced by different factors like cultural mindset (i.e., how people are willing to step back and putting external ideas and vendors in the center of innovation) or technical capabilities (i.e., the availability of developer portals, open APIs, collaboration tools).* $v$ *impacts the cash flows differently: it strengthens the positive impact of OI, decreasing* $I_0(\lambda_1)$ *and* $M(\lambda_1, \lambda_2)$, *and weakens the negative impact of OI, increasing* $CC_I(\lambda_1)$ *and* $CC_D(\lambda_2)$. *The positive impact of* $v$ *on* $S(\lambda_1, \lambda_2)$ *can be reflected in the higher success probability of OI application* $p$. *Thus, we modify the success probability* $p$ *as* $p(v) = p^{(1-0.5*v)}$ *with* $0 < p(v) < 1$. *Hence, the opposite probability of failure to satisfy the laws of probability is* $1 - p(v)$.

Figures II.1-1 – II.1-3 illustrate the cause-effect-relationships between the degree of openness $\lambda_i$, the ability factor $v$, and the outlined cash flows. These relationships are based on findings from existing literature (Enkel et al., 2005; Laursen and Salter, 2006; Gassmann et al., 2010), and can be modeled differently, as discussed below.

Figure II.1-1 exemplifies the impact of $\lambda_i$ and $v$ on $I_0(\lambda_1)$ and $M(\lambda_1, \lambda_2)$, respectively.

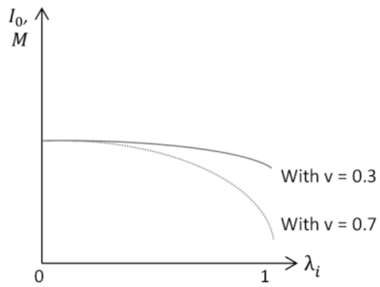



**Figure II.1-1:** Impact of $\boldsymbol{\lambda_i}$ and $\boldsymbol{v}$ on $\boldsymbol{I_0(\lambda_1)}$ and $\boldsymbol{M(\lambda_1, \lambda_2)}$

Regarding the impact of $\lambda_i$ and $v$ on $I_0(\lambda_1)$ and $M(\lambda_1, \lambda_2)$, respectively, we assume a decreasing concave function, as more openness and a higher ability to manage OI result in more cost-saving potential. We abstain from using a linear function to model this relationship, as this would imply the same strong impact of OI at any point on the continuum between completely closed and completely OI modes; for example, the first integrated external stakeholder has the same impact as later ones. However, a company that intensively collaborates with external stakeholders has more cost-sharing potential and resource synergies for $I_0(\lambda_1)$ than a company that only conducts a few subprojects with one external stakeholder. Similarly, regarding $M(\lambda_1, \lambda_2)$, external stakeholders engaged in intensive collaborations are often more familiar with a new product and can more effectively promote it on the market than external stakeholders, who are involved only in few subprojects. Thereby, $v$ strengthens this effect.

An exemplary analytical form for this relationship could be:

$$I_0(\lambda_1) = I_0 * (1 - 0.5 * \lambda_1 * v)^{0.5}$$

$$M(\lambda_1, \lambda_2) = M * (1 - 0.5 * \lambda_1 * v)^{0.5} * (1 - 0.5 * \lambda_2 * v)^{0.25}$$

The translation of cause-effect-relationships discussed in previous literature into analytical equations for a mathematical model undoubtedly requires some generic assumptions, which are not yet based on an empirical analysis. Thus, they should be considered as a theoretical approximation to depict these relationships and convert them into a mathematical model. Clearly, these functions in practice should be carefully estimated relative to the company's and project's idiosyncrasies, and all parameters should be adjusted according to the expected impact potential of OI application.

Figure II.1-2 exemplifies the impact of $\lambda_i$ and $v$ on $CC_I(\lambda_1)$ and $CC_D(\lambda_2)$.

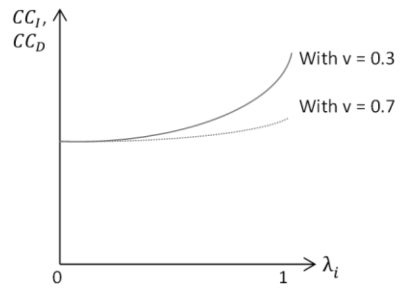



**Figure II.1-2:** Impact of $\boldsymbol{\lambda_i}$ and $\boldsymbol{v}$ on $\boldsymbol{CC_I(\lambda_1)}$ and $\boldsymbol{CC_D(\lambda_2)}$

Regarding the impact of $\lambda_i$ with $i = 1,2$ and $v$ on $CC_I(\lambda_1)$ and $CC_D(\lambda_2)$, respectively, we assume an increasing convex function, as more openness results in higher coordination costs. While initial collaboration activities already lead to increasing $CC_I(\lambda_1)$ and $CC_D(\lambda_2)$, the more ITIP subprojects that open, the stronger the coordination costs increase, whereby $v$ weakens this effect. An exemplary analytical form could include the following:

$$CC_I(\lambda_1) = CC_I * (1 - \lambda_1^2 * ln\,(0.5 * v))$$

$$CC_D(\lambda_2) = CC_D * (1 - \lambda_2^2 * ln\,(0.5 * v))$$

The impact of $\lambda_i$ is modeled as an increasing concave function for an upside scenario $S^u(\lambda_1, \lambda_2)$, as more openness results in higher sales, with decreasing marginal profit (see Figure II.1-3). An exemplary analytical form could be:

$$S^u(\lambda_1, \lambda_2) = S * (1 + ln(1 + \lambda_1)) * (1 + ln(1 + 0.5 * \lambda_2))$$

The impact of $\lambda_i$ is modeled as a decreasing concave function for a downside scenario $S^d(\lambda_1, \lambda_2)$, as more openness results in lower sales $S^d(\lambda_1, \lambda_2)$ (see Figure II.1-3). An exemplary analytical form could be:

$$S^d(\lambda_1, \lambda_2) = S * (1 - \lambda_1)^\alpha * (1 - 0.5 * \lambda_2)^\alpha$$

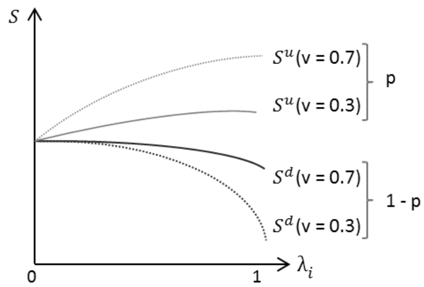



**Figure II.1-3:** Impact of $\boldsymbol{\lambda_i}$ and $\boldsymbol{v}$ on $\boldsymbol{S^u(\lambda_1, \lambda_2)}$ and $\boldsymbol{S^d(\lambda_1, \lambda_2)}$

Although we assume a risk-neutral company, the parameter $\alpha$ with $0 < \alpha < 1$ can be considered a weighting parameter for the downside scenario. Thus, a higher $\alpha$ depicts how much the cash inflows from sales decrease with a failed OI application. Thus, a higher $\alpha$ indicates a considerably stronger decrease in $S(\lambda_1, \lambda_2)$ (e.g., due to knowledge depletion) and can be interpreted as an indicator of an ITIP's strategic importance (e.g., for the core business).

The impact of $v$ is indirectly modeled through $p$, as a higher ability to manage OI increases the OI application's probability of success. An exemplary analytical form for the cash inflows $S(\lambda_1, \lambda_2) \geq 0$ could be:

$$S(\lambda_1, \lambda_2) = p^{(1-0.5*v)} * S^u + \left(1 - p^{(1-0.5*v)}\right) * S^d$$

We illustrate the impact of $\lambda_i$ and $v$ on the cash flows by using the exemplary analytical forms as described above. Thus, for brevity we base these on common functions, such as the quadratic or ln functions, to depict the non-linear relationships between $\lambda_i$ and $v$ and the cash flows. We further illustrate the decreased impact of applying OI in the development phase on cash flows through a lower power or lower multiplier for $\lambda_2$. We use a multiplier of 0.5 as a starting point to avoid an excessively strong impact of $\lambda_i$ and $v$ on the cash flows. Table II.1-1 summarizes the considered parameters.

| | |
|---|---|
| $I_0(\lambda_1) \geq 0$ | cash outflows for project initiation costs |
| $CC_I(\lambda_1) \geq 0$ | cash outflows for coordination costs in the idea generation phase |
| $CC_D(\lambda_2) \geq 0$ | cash outflows for coordination costs in the development phase |
| $M(\lambda_1, \lambda_2) \geq 0$ | cash outflows for marketing costs |
| $S(\lambda_1, \lambda_2) \geq 0$ | cash inflows from sales as perpetuity |
| $S^u(\lambda_1, \lambda_2) \geq 0$ | cash inflows from sales with successful OI application (upside scenario u) |
| $S^d(\lambda_1, \lambda_2) \geq 0$ | cash inflows from sales with failed OI application (downside scenario d) |
| $0 \leq \lambda_1 \leq 1$ | degree of openness in the idea generation phase |
| $0 \leq \lambda_2 \leq 1$ | degree of openness in the development phase |
| $0 < v < 1$ | ability to manage OI |
| $0 < p < 1$ | probability of success in OI application |
| $0 < p(v) < 1$ | modified probability of success in OI application |
| $0 < \alpha < 1$ | weighting parameter for the downside scenario $S^d$ |
| $0 < r \leq 1$ | discount rate |

**Table II.1-1:** Summary of the model parameters

II.1.3.2.3. Objective Function

We consider the expected NPV by maximizing the following objective function relative to $\lambda_1$ and $\lambda_2$. We discount the cash flows by assuming that $I_0(\lambda_1)$ is realized in t = 0, $CC_I(\lambda_1)$ in t = 1, $CC_D(\lambda_2)$ and $M(\lambda_1, \lambda_2)$ in t = 2, and $S$ from t = 3 on.

$$NPV_0(\lambda_1, \lambda_2) = -I_0(\lambda_1) + \frac{-CC_I(\lambda_1)}{1+r} + \frac{-CC_D(\lambda_2) - M(\lambda_1, \lambda_2)}{(1+r)^2} + \frac{S(\lambda_1, \lambda_2)}{r * (1+r)^2} \quad \rightarrow max!$$

## II.1.4 Model Analysis

Our analysis first determines the optimal degree of openness $\lambda_i^*$ with $i = 1, 2$ for an ITIP by inserting initial values (c.f., Table II.1-2) in the exemplary functions for cash flows and maximizes the objective function, as aforementioned. We then analyze the impact of different degrees of openness on the optimal NPV. We thereafter broaden our analysis by conducting a sensitivity analysis and Monte Carlo simulation to examine the selected model parameters' influence on the optimal degree of openness, and to analyze the distribution of the optimal degree of openness. We conclude by analyzing the optimal degree of openness and associated NPV for some scenarios.

We are aware that using fictitious input values and values gathered through a Monte Carlo simulation can only be a first step, and cannot completely depict the overall variety of idiosyncrasies in real-world ITIPs. Nevertheless, our analysis can demonstrate how companies can enhance their decision making on OI application in ITIPs by taking into account the idiosyncrasies within an *ex ante* financial evaluation.

#### *II.1.4.1 Model analysis for initial values*

We provide initial input data for our model by considering a real-life case involving a branch-centric banking group. Its digital strategy includes launching a mobile-only banking proposition that purely focuses on a mobile user experience (UX) and usage across all products and services (e.g., registration, credit card management, and loan application), and evaluates applying OI within the ITIP.

The banking group already in the idea generation phase aims to integrate a potential future user group to identify a suitable value proposition, use cases and UX of the IT innovation. An early user platform is created, in which users' ideas are discussed and ranked, and initial mock-ups are tested. Moreover, live events and customer insights are organized, where early users can test specific concepts and discuss feature roadmaps, as well as the most promising UX in A/B testing and laboratories. To realize this, a dedicated agile "squad" team, including moderators, designers, and business analysts, must be established and coordinated. Further, tools and platforms must be evaluated, licensed, planned, established, and maintained. As the bank already has a dedicated digital initiatives team and experts who can easily set up the platform in-house, it assumes that $I_0(\lambda_1)$ is rather low and decreases with greater openness (i.e., including more testers or organizing more events) as fixed costs are better distributed. Further, $CC_I(\lambda_1)$ is rather high and increases with more openness as leaks and early insights become more likely, which requires lawsuits or PR activities, among others.

The banking group further considers applying OI in the development phase. Therefore, the IT infrastructure is extended with open APIs, including a sandbox where external developers can test and develop new features. Further, crowd-testing platforms are used to distribute the test effort among a mass of potential users, which also addresses the variety of different mobile devices and operating systems in the market. As this approach requires establishing and coordinating an open API platform, user feedback, and test results, the bank assumes that $CC_D(\lambda_2)$ is rather high and increases with more openness due to an increased coordination of test results and risk of knowledge leaks. In addition to such traditional marketing expenditures as print ads, the initiative also includes expenditures for influencers, such as bloggers, speakers, and opinion leaders. These influencers receive early access to the product to test it and discuss it at conferences, write blog articles, and distribute their opinions via social networks, like Twitter. Due to the generally high attention to new IT services, the bank assumes that $M(\lambda_1, \lambda_2)$ is rather low and decreases with more openness as word-of-mouth, member-gets-member, sharing, and influencer activities lead to some self-marketing, and thus, lower customer acquisition costs.

The $S(\lambda_1, \lambda_2)$ is considered low due to the high competitive pressure, and consequently rather low margins, in the mobile banking market. Various customers in the upside scenario $S^u(\lambda_1, \lambda_2)$ are familiar with the product through openness, and are excited about the commercial launch. Thus, a loyal customer base can be quickly installed and high revenues can occur through an active and ongoing product use (e.g., credit card fees or interest income). High expectations cannot be met in the downside scenario $S^d(\lambda_1, \lambda_2)$, as only the IT-affine beta users have been excited, but the mass is not sufficiently "digital," and thus, unwilling to adapt a mobile-only approach. Finally, we assume a rather low $\alpha$ as the approach does not affect the core business. Table II.1-2 summarizes these and further initial values.

| Parameter<br>(cash flows in TEUR) | Initial Value | Range | Distribution |
|---|---|---|---|
| $I_0$ | 200 | 0 – 400 | equal |
| $CC_I$ | 700 | 0 – 1,400 | equal |
| $CC_D$ | 800 | 0 – 1,600 | equal |
| $M$ | 100 | 0 – 200 | equal |
| $S$ | 200 | 0 – 400 | equal |
| $v$ | 0.5 | 0 – 1 | triangular |
| $p$ | 0.5 | 0 – 1 | triangular |
| $\alpha$ | 0.25 | 0 – 1 | equal |
| $r$ | 0.1 | not simulated | not simulated |

**Table II.1-2:** Data for the Monte Carlo simulation and analysis

By placing the initial values in the objective function, we determine the theoretically optimal degree of openness $\lambda_i^*$ for $i = 1, 2$ as well as the corresponding NPV, as Table II.1-3 demonstrates. In terms of interpreting these results, $\lambda_1^* = 0.34$ and $\lambda_2^* = 0.26$ mean that the bank achieves the maximal project's NPV (278 TEUR) by opening 34% and 26% of subprojects in the idea generation and development phases, respectively. We observe that the NPV with the optimal degree of openness is considerably higher than the NPV of completely closed and completely OI projects. This observation supports Laursen and Salter's (2006) empirical findings, in that too much openness can negatively affect innovative performance (and consequently, financial performance), due to the greater effort required to manage too many search channels. We are aware that these results might be ad-hoc challenging to interpret and to operationalize in practice with regards to opening exactly 34% and 26% of the ITIP, respectively. However, it gives the decision-maker a valuable hint for the general usefulness of applying OI in different phases and also about the level of openness that needs to be considered – even though it can always only be a proxy for the actual openness.

| | CI | $(\lambda_1^*; \lambda_2^*)$ | OI |
|---|---|---|---|
| $NPV_0(\lambda_1, \lambda_2)$, TEUR | 73 | 278 | -997 |
| $\lambda_1$ | 0.00 | 0.34 | 1.00 |
| $\lambda_2$ | 0.00 | 0.26 | 1.00 |

**Table II.1-3:** Degree of openness and rounded NPVs for closed, mixed, and open strategies

We then analyze the OI application in different phases of the innovation process and its impact on the project's NPV. First, we partially maximize the NPV relative to $\lambda_2^*$, holding $\lambda_1 = 0$ constant, and vice versa. Table II.1-4 illustrates that, compared to an ITIP with optimal degrees of openness for both phases, a completely closed idea generation phase ($\lambda_1 = 0$) leads to a considerably lower NPV = 113 TEUR. Conversely, a completely closed development phase ($\lambda_2 = 0$) also leads to a lower NPV = 205 TEUR. Thus, we observe that applying OI in only one phase of the ITIP can add value, as the related NPVs are positive. However, a considerable reduction in NPV (Δ = 165 TEUR) without applying OI in the idea generation phase allows us to state that a completely closed idea generation phase has a higher negative impact on the project's NPV as a completely closed development phase (Δ = 73 TEUR). This observation parallels Enkel et al.'s (2005) assertion that it is more beneficial to apply OI in the early phases of the innovation process.

| | $(\lambda_1^*; \lambda_2^*)$ | $(\lambda_1 = 0; \lambda_2^*)$ | $(\lambda_1^*; \lambda_2 = 0)$ |
|---|---|---|---|
| $NPV_0(\lambda_1, \lambda_2)$, TEUR | 278 | 113 | 205 |
| $\lambda_1$ | 0.34 | 0.00 | 0.32 |
| $\lambda_2$ | 0.26 | 0.20 | 0.00 |

**Table II.1-4:** Relationship between $\boldsymbol{\lambda_1^*}$ and $\boldsymbol{\lambda_2^*}$

### *II.1.4.2 Sensitivity analysis for selected model parameters*

This section analyzes the impact of the ability to manage OI $v$ and the probability of success in OI application $p$ on the optimal degree of openness $\lambda_i^*$ with $i = 1, 2$ and the associated project's NPV. We accomplish this by conducting a sensitivity analysis for $v$ and $p$, and alternating one parameter ceteris paribus in the range between 0 and 1.

Figure II.1-4 indicates that a higher $v$ leads to higher $\lambda_1^*$ and $\lambda_2^*$. Thus, the bank tends to be more open, with a higher ability to manage OI. While this result is not surprising, it demonstrates that the model correctly depicts reality; moreover, it clearly illustrates the strength and nature of this relationship. Further, we observe that even with the perfect ability to manage OI ($v = 1$), the bank should not completely open the ITIP due to the high coordination costs.

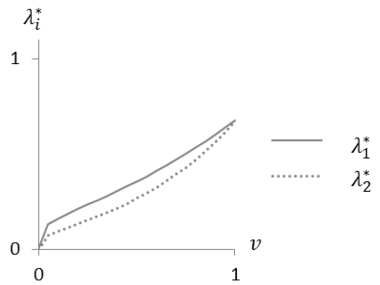



**Figure II.1-4:** Impact of $\boldsymbol{v}$ on $\boldsymbol{\lambda_1^*}$ and $\boldsymbol{\lambda_2^*}$

Figure II.1-5 illustrates that a higher $p$ also leads to higher $\lambda_1^*$ and $\lambda_2^*$. Thus, the bank tends to be more open, with a higher probability of success in OI application. This result is also anticipated but reasonable, as the probability of success in OI application $p$ directly influences the cash inflows, and thus, the NPV. Similar to $v$, the certainty regarding the success of OI application ($p = 1$) does not necessary lead to a completely open ITIP. We can conclude that both parameters strongly influence the optimal degree of openness and project NPV. Thus, the bank should strongly work on improving $v$ and $p$ to increase the NPV. One measure for reaching that goal could be establishing an OI culture and standardizing OI processes.

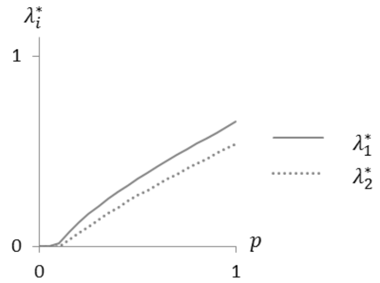



**Figure II.1-5:** Impact of $\boldsymbol{p}$ on $\boldsymbol{\lambda_1^*}$ and $\boldsymbol{\lambda_2^*}$

### *II.1.4.3 Model analysis through a Monte Carlo simulation*

We conduct a Monte Carlo simulation in the next step by randomly varying all model parameters except the discount rate r. Further, we generated 1,000 scenarios to ensure a reliable basis for our analysis. For most parameters, we assume an equal distribution to cover a broad range of possible project scenarios. We assume a triangular distribution for $v$ and $p$, as they rather lie between zero and one as at extremes (see Table II.1-2).

We observe that the optimal degree of openness $\lambda_i^*$ with $i = 1, 2$ covers the complete possible range between zero and one (see Figure II.1-6 and Figure II.1-7). Therefore, the bank achieves the maximal project's NPV for different project settings by opening none, some, or all subprojects. This finding parallels Dahlander and Gann (2010) and Schroll and Mild (2012), who note that it is more reasonable to consider various degrees of openness than only closed versus OI. Further, the histograms for $\lambda_1^*$ and $\lambda_2^*$ are slightly asymmetrical, with a higher share of values in the range between 0 and 0.5. Given our parameterization, this means that the bank should open a mean 33% and 32% of subprojects in the idea generation and development phases, respectively. This finding underlines the need to mindfully apply OI instead of opening the entire innovation process, which parallels findings by Enkel et al. (2005) and Laursen and Salter (2006).

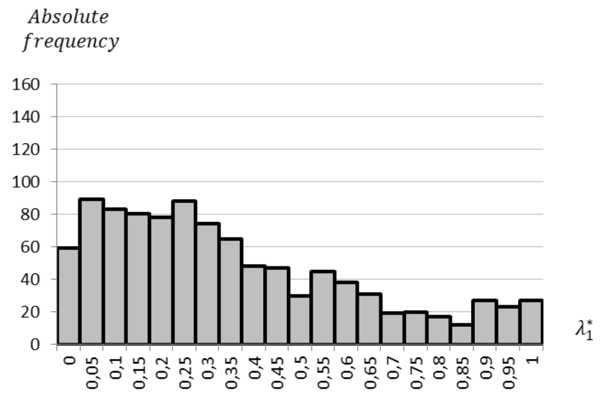



**Figure II.1-6:** Histogram for $\boldsymbol{\lambda_1^*}$ after the Monte Carlo simulation

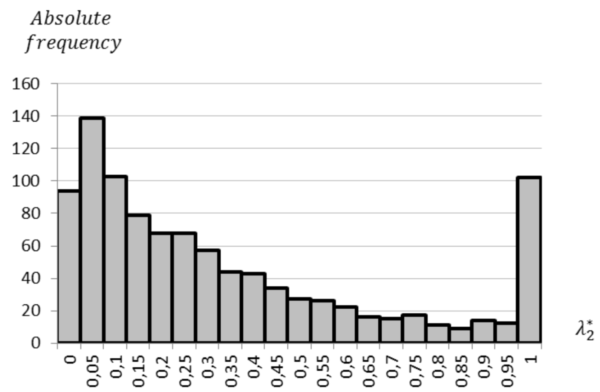
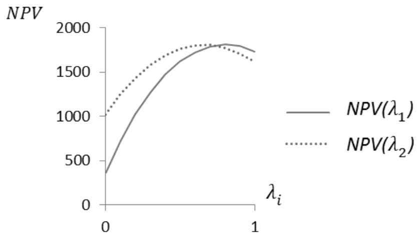



**Figure II.1-7:** Histogram for $\boldsymbol{\lambda_2^*}$ after the Monte Carlo simulation

In contrast to $\lambda_1^*$, the histogram for $\lambda_2^*$ indicates that a high share of values lies near one. As opening the project in the development phase is less beneficial but also less risky, more project settings exist in which a completely opened development phase leads to a maximal NPV.

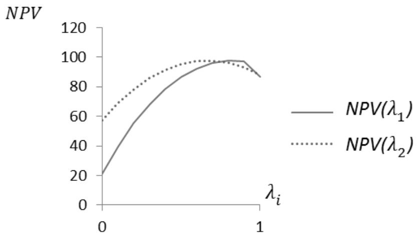
However, our model considered rather broad ranges for cash flows in its simulation to cover a wide range of possible project settings. Companies in a real-world setting require a careful estimation of model parameters to obtain more precise results and drive more precise analyses. We illustrate the impact of projects' and companies' characteristics on the optimal degree of openness by further considering different scenarios. First, we consider when the mobile banking proposition is a strategic project with high benefits and costs as well as a high-weighting parameter for OI failure. This contrasts a non-strategic project, in which these parameters are low. We further consider scenarios in which the bank is experienced versus unexperienced in applying OI. Figure II.1-8 summarizes the results for these scenarios.

**Scenario 1:**
**Strategic Project, High Experience in Applying OI**
$I_0 = 400;\ CC_I = 1{,}400;\ CC_D = 1.600;\ M = 200;\ S = 400;$
$v = 0.7;\ p = 0.9;\ \alpha = 0.9$



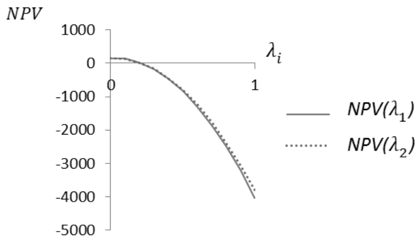

$\lambda_1^* = 0.80;\ \lambda_2^* = 0.66;\ NPV(\lambda_1^*;\lambda_2^*) = 1{,}810$

**Scenario 3:**
**Non-strategic Project, High Experience in Applying OI**
$I_0 = 20;\ CC_I = 70;\ CC_D = 80;\ M = 10;\ S = 20;$
$v = 0.7;\ p = 0.9;\ \alpha = 0.1$



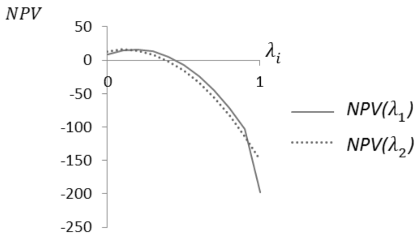

$\lambda_1^* = 0.82;\ \lambda_2^* = 0.67;\ NPV(\lambda_1^*;\lambda_2^*) = 98$

**Scenario 2:**
**Strategic Project, Low Experience in Applying OI**
$I_0 = 400;\ CC_I = 1{,}400;\ CC_D = 1.600;\ M = 200;\ S = 400;$
$v = 0.1;\ p = 0.5;\ \alpha = 0.9$




$\lambda_1^* = 0.03;\ \lambda_2^* = 0.02;\ NPV(\lambda_1^*;\lambda_2^*) = 152$

**Scenario 4:**
**Non-strategic Project, Low Experience in Applying OI**
$I_0 = 20;\ CC_I = 70;\ CC_D = 80;\ M = 10;\ S = 20;$
$v = 0.1;\ p = 0.5;\ \alpha = 0.1$




$\lambda_1^* = 0.21;\ \lambda_2^* = 0.11;\ NPV(\lambda_1^*;\lambda_2^*) = 16$

**Figure II.1-8:** Results for considered scenarios

Figure II.1-8 reveals the optimal degree of openness, which varies depending on the project type (strategic versus non-strategic): a high degree of openness for both project types when experience and the probability of success are high in Scenarios 1 and 3, versus a low degree of openness for all project types for low experience and probability of success in Scenarios 2 and 4.

While a substantial experience bank can result in a positive NPV, even when the theoretical optimum is missed, a low experienced bank generates massive NPV losses, even with small deviations from the optimum (Scenarios 2 and 4). These results again highlight the importance of steady OI engagement to increase its success in application. In summary, our results parallel those from Laursen and Salter (2006), who indicate an inverted U-shaped relationship between the degree of openness and the company's innovation performance.

### II.1.5 Implications

#### *II.1.5.1 General implications and remarks*

The general goal of this paper is measuring the impact of applying OI in ITIPs through quantitative financial methods (like NPV) from an *ex ante* perspective. Such approaches require the application of methods that are based on assumptions and thus partly abstract from reality. However, we contribute both to academic research as well as to practical decision-support as our approach shows that such methods in general can be used to measure the outcome of applying OI in ITIPs. Furthermore, we demonstrate that is worthwhile to measure the application of OI from an *ex ante* perspective and not limiting it to *ex post* reviews. Moreover, to consider an ITIP's idiosyncrasies, the effects of OI activities should be measured at project level and not only be evaluated on a company level.

In addition, our approach supports the understanding of the circumstances that determine the ideal openness level. As our analysis shows, the ideal openness level depends on company's ability to manage OI that can incorporate different issues like organizational (e.g., processes), cultural (e.g., innovation mindset), and technological (e.g., API for third party integration) maturity. Besides that, there is not 'the' ideal level of openness but an 'ideal' level within each project phase, within each project type (in our case ITIPs) and also company type, industry, or size.

#### *II.1.5.2 Contribution to academic literature and further research*

From an academic perspective, the results of our work contribute to a broad range of research in the field of OI, IT innovation as well as research & development. It provides a supporting evidence of past findings, based on monetary evaluations and thus strengthens general outcomes of prior research that too much openness can be negative for innovation, and consequently for financial performance, due to a disproportionate increase in costs and risks (Laursen and Salter, 2006; Patrakosol and Olson, 2007). Our analysis also shows that the optimal degree of openness ranges between closed and completely open and is in line with outcomes of Laursen and Salter (2006) and Lazzarotti and Manzini (2009).

Despite the mentioned limitations, our model sets the basis for further investigations by academics in the future, for example, by enriching it with further variables and challenging the assumptions in real-world scenarios as described in Section 6. Furthermore, the external validity of both our analysis and the gained insight should be strengthened as well as the model's practical usability should be further examined.

From a methodological point of view, an empirical validation of the causal relationships analyzed in our model (e.g., identifying appropriate functions and further influential factors) could be further researched to surpass our limitation of applying fictitious input values and exemplary functions. Another aspect of further research should consider how the ability to manage OI can be measured (e.g., through maturity models or balanced scorecards) and its key drivers (e.g., cultural, governance or IT).

Finally, we propose that future research considers the idiosyncrasies of different ITIP types, such as IT product, service, and process innovation, to compare their degrees of openness. Our analysis does not detail other aspects, including the types of OI activities and external stakeholders, which might also help to specify the model.

#### *II.1.5.3 Decision-support for practitioners*

Practitioners can apply our approach as a first step to measure the value contribution of applying OI in their ITIPs while considering important success drivers and idiosyncrasies of ITIPs instead opening them on a gut feeling.

Thereby, they can use it for a flexible and project-specific evaluation and for a re-evaluation of running projects to fine-tune the level of openness in different project phases. They can do this like the bank in the real-life case described in Section 4.1 by estimating the project cash flows and other model parameters summarized in Table II.1-2. For more precise measurement, the practitioners should adapt our approach to their real-world use cases. For that, they should estimate and adjust the functions for modeled relationships according to the expected impact potential of OI application (e.g., the values of cash flows, which can be achieved through OI).

Even though the outcome might be challenging to interpret and to operationalize exactly in practice, the practitioners can still use it as an indicator or proxy for the appropriate level of OI in different project phases. It also can help to derive appropriate internal measures for improving the company's chances to achieve positive results from applying OI (e.g., enhancing the openness culture, technical access for third parties, crowd-based testing). They further can use our model to analyze how deviations from the theoretical optimum affect the resulting cash flows and consequently NPV. Though the model in reality might not be able to deliver exact figures, it supports a sound OI application and does not leave the project owner alone with a gut feeling.

Decision-makers can further use our approach for internal stakeholders to persuade them about the validity of the proposed or followed OI strategy. For that purpose, they can drive scenario analyses as described in Section 4.3 to illustrate the impact of projects' and companies' characteristics and especially the idiosyncrasies of ITIPs on the optimal degree of openness. Our analysis in Section 4 exemplarily demonstrates how companies can incorporate these into the *ex ante* financial evaluation of applying OI.

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 be further used to underpin the need of a steady improvement in managing OI, for example, by providing measurement concepts like maturity models or balanced scorecards. Furthermore, institutionalizing and establishing long-term, trustworthy collaborations and cultural mindset supported by an open API based technological platform are further drivers for successful application of OI.

### II.1.6 Limitations and outlook

Although our approach provides initial insights and an evaluation of applying OI in ITIPs, and serves as a starting point for further investigations, it has some limitations.

First, our model considers five types of cash flows that occur within three phases of the innovation process, and discounts them over three periods. In practice, companies deal with various cash flows, which are often difficult to estimate and allocate. Thus, our model can be enriched by considering further cash flows (e.g., the development costs in the development phase or customer service in the commercialization phase). Additionally, companies can further detail our model's number of project phases, incorporate non-deterministic costs, consider different levels of willingness to carry risks instead of assuming risk-neutrality, or incorporate the product life cycle characteristics in opposition to the cash inflows from modeled as a perpetuity.

Despite these limitations, our work provides a formal analysis and initial insights into a well-founded *ex ante* evaluation of opening ITIPs. It also indicates a further basis for research aimed at closing the aforementioned research gap.

### II.1.7 Acknowledgments

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



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| Major revision in: | International Journal of Innovation and Technology Management |



**Abstract:** *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 IT-related innovation project (ITIP). To address this question, we provide an approach for an ex ante financial evaluation of ITIPs related to the team design. For that, we develop a model that determines the optimal team design for an ITIP by considering the associated benefits and costs and their impact on profit. We examine relevant causal relationships by analyzing 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.*

### II.2.1 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 increases 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 setted 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 discussion on 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. Is also allows to compare 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 to a rational, strategic decision. Therefore, we apply sensitivity analyses and analyze 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 industry company, the second one from a small start-up company in 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 the 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 analyze our theoretical model to answer the stated research questions. We conclude by discussing the contributions to research and practice, limitations and future research potential.

### II.2.2 Theoretical Background and Related Work

As teams plays a crucial role in innovation projects, the 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 analyzing 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 behavior-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 varies. 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 background 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 increasing 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 the most research on team effectiveness focuses on face-to-face teams, increased globalization 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 background 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 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 an 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 measure for effectiveness of members' observable goal-directed team behavior (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 the 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 analyzing 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 analyzing 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 organizational 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 analyze 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.

### II.2.3 Toward an Optimal ITIP Team Design

#### *II.2.3.1 Research Methodology*

We base on a normative analytical modeling 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 analyze 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 analyze 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).

#### *II.2.3.2 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 analyze 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 $P \in \{2,3,..,n\}$. 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 $\vec{\mathrm{w}}^{\mathrm{T}} = (\mathrm{w_1}, \mathrm{w_2}, \dots, \mathrm{w_P}) \in \mathbb{R}^+$ 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 $\mathrm{g_{ij}} \in [0, 1]$. Thereby, $\mathrm{g_{ij}}$ reflects the degree to which the regional market assessment capabilities of each team member coincide with each ones of the other team members. Therefore, $\mathrm{g_{ij}} = 1$ 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, $\mathrm{g_{ij}} = 0$ 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, $\mathrm{g_{ij}}$ 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, $\mathrm{g_{ij}}$ would have a value close to 0. The team's geographical background diversity is $\mathrm{g} =$

$\sum_{i=1}^{n}\sum_{j=1}^{n} g_{ij} - P * (P^2 - P)^{-1}$ 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 $RC_{P_i} \in \mathbb{R}^+$ 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 $S_i \in \mathbb{R}^+$. 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 $\epsilon\ \mathbb{R}^+$ 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 $\epsilon\ \mathbb{R}^+$ 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 II.2-1 demonstrates the approach.

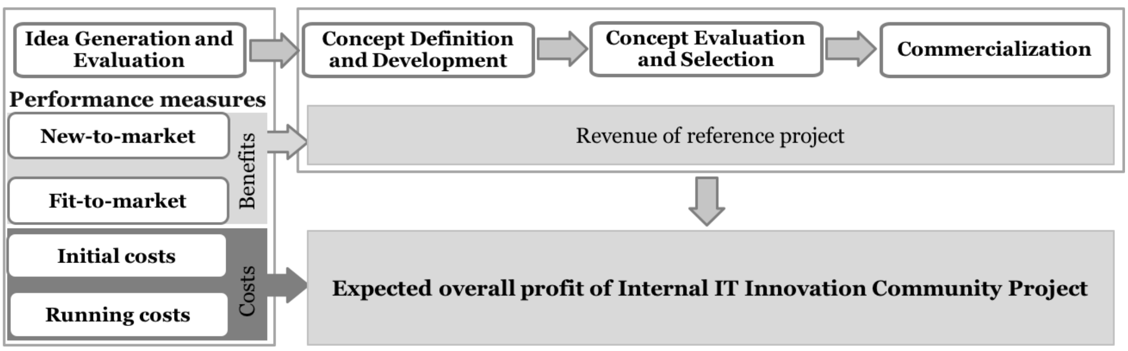


**Figure II.2-1:** Reference project approach to measure overall profit

*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 II.2-2 illustrates two exemplary s-curves for a reference project with $\mathrm{P_{RP}} = 6$.

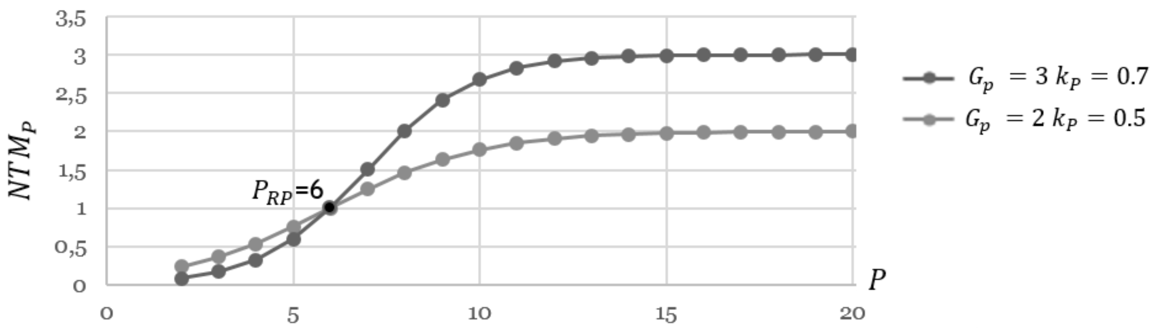


**Figure II.2-2:** Exemplary s-curves for the influence of the team size on the NTM factor

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 $w_m \epsilon \mathbb{R}^+$ and follows an s-curve: $FTM_{w_m}(w_m) = G_{w_m} * \left(1 + e^{k_{w_m}(b_{w_m} - w_m)}\right)^{-1}$ with $FTM_{w_m}(w_m) \epsilon \mathbb{R}^+$. Thereby, $G_{w_m}, b_{w_m}$ and $k_{w_m}$ as well as the s-curve effect can be interpreted analogously to assumption 7. The assumed influence of $w_m$ 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, $w_m$ 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 $w_d \epsilon \mathbb{R}^+$ and follows an s-curve: $NTM_{w_d}(w_d) = G_{w_d} * \left(1 + e^{k_{w_d}\left(b_{w_d} - w_d\right)}\right)^{-1}$ with $NTM_{w_d}(w_d) \epsilon \mathbb{R}^+$. Thereby, $G_{w_d}, b_{w_d}$ and $k_{w_d}$ as well as the s-curve effect can be interpreted analogously to assumption 7. The assumed positive relationship between $w_d$ 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, $w_d$ 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 $g \epsilon (0,1]$ and follows an s-curve: $FTM_g(g) = G_g * \left(1 + e^{k_g(b_g - g)}\right)^{-1}$ with $FTM_g(g) \epsilon \mathbb{R}^+$. An increasing g implies a decreasing degree of geographical diversity. Thereby, $G_g, b_g$ and $k_g$ as well as the s-curve effect can be interpreted analogously to assumption 7. However, $k_g \epsilon \mathbb{R}$ 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 $k_g < 0$ (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 $k_g > 0$. 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 $a \in (0,1]$ and follows an inverse u-curve: $NTM_a(a) = (1 - G_a) * (b_a - k_a)^{-2} * (a - b_a)^2 + G_a with NTM_a(a) \in \mathbb{R}^+$. Thereby, $k_a \in [0;1]$ and $G_a \geq 1$, determine the u-curve's vertex at $(k_a|G_a)$ and therefore the point until which the marginal utility of $NTM_a(a_{RP})$ increases with an increasing a and vice versa. Furthermore, we assume $b_a = a_{RP}$, due to $NTM_a(a_{RP}) = 1$. 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 II.2-3 summarizes the assumptions, parameters and their impact on the benefits and costs.

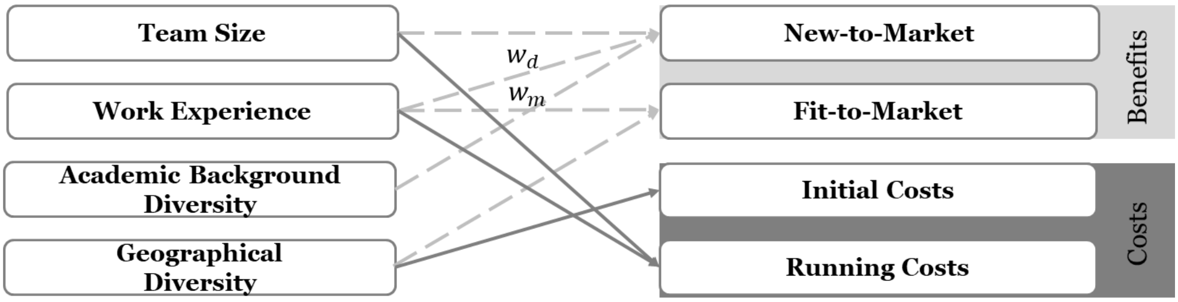


**Figure II.2-3:** Relevant parameters and their relationships to benefits and costs

*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.

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

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

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

$$\Delta R_{FTM_f} = (1{-}\propto) FTM_f(f_{ITIP}) - 1$$

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

Thereby, $\Delta R_{NTM_n}$ and $\Delta R_{FTM_f}$ 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 II.2-1 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 $f \in \{w_m, \mathrm{g}\}$ ) |
| $IC(g)$ | 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 $\mathrm{n} \in \{\mathrm{P}, \mathrm{w_d}, \mathrm{a}\}$ $\forall$ $\mathrm{f} \in \{\mathrm{w_m}, \mathrm{g}\}$ ) | |
| $RC_{P_i}$ | 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 II.2-1:** Summary of major Parameters

### *II.2.3.3 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 II.2-2 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.

<table>
<tr><td>Expert 1: Large industry company</td><td>Expert 2: Small start-up for financial services</td></tr>
<tr><td colspan="2">Assumption 1 - Relevant ITIP team design parameters</td></tr>
<tr><td>• The considered team design parameters are relevant in practice.<br>• 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).<br>• Additionally, the working environment like (IT) infrastructure, tools and managerial attention may have a significant influence on team performance (see subsequent discussion).</td><td>• The considered team design parameters are relevant in practice.<br>• 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).<br>• 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 containted 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).<br>• 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).</td></tr>
<tr><td colspan="2">Assumption 2-4 - Costs of an ITIP & cause-effect-relationships on costs</td></tr>
<tr><td>• The considered cost drivers are relevant in practice.<br>• Furthermore, the running costs after the new product or service launch, e.g. maintenance service, may be considered (see subsequent discussion).</td><td>• The considered cost drivers are relevant in practice.<br>• 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).<br>• 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 $RC_{P_i}$).<br>• 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 $S_i$).<br>• 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 $IC_{gi}$).</td></tr>
</table>

| Assumption 5 - Benefits | |
|---|---|
| • The assumption is meaningful.<br>• The number of generated ideas and the time-to-market might be considered as further benefits (see subsequent discussion).<br>• The risk aspect of a high NTM strategy might be considered (see subsequent discussion). | • The assumption is meaningful.<br>• 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.<br>• 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).<br>• 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).<br>• 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).<br>• 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 communication and coordination costs (can be considered in our model by an appropriate parameterization of assumption 7). | • The assumptions are basically meaningful and recognizable in practice.<br>• 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). |

**Table II.2-2:** 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'.

### II.2.4 Model Evaluation

In this section, we demonstrate the functionality of our model and analyze 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 II.2-3 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 $FTM_f$ and $NTM_n$ with $n \in \{P, w_d, a\}\ \forall f \in \{w_m, g\}$ | | | |
|---|---|---|---|---|---|---|---|
| $P_{RP}$ | 6 | $a_{RP}$ | 0.9 | G | 2 | | |
| $w_{m_{RP}}$ | 20 | $g_{RP}$ | 1 | k | 0.5 for $k_P, k_{w_d}, k_{w_m}, k_a$ and -5 for | | |
| $w_{d_{RP}}$ | 5 | | | b | b is equal to particular parameter of | | |
| Company-specific parameters to determine costs | | | | Objective Function | | | |
| $RC_{P_i}$ | $ 100 | $IC_{gi}$ | $ 1,000 | $R_{RP}$ | $ 1000 | $\propto$ | 0.2 |
| $IC_i$ | $ 500 | $S_i$ | 0.2 | | | | |

**Table II.2-3:** Parameter setting for the initial scenario

### *II.2.4.1 Ex ante analysis of the optimal design of an ITIP*

Based on the initial scenario (see Table II.2-3), 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 II.2-4 shows the optimal parameter values and the related profit. For our analysis, we limited the team's work experience diversity $w_d \in \mathbb{R}^+$ 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 | | | | |
|---|---|---|---|---|
| $P_{ITIP}$ | $w_{m_{ITIP}}$ | $w_{d_{ITIP}}$ | $a_{ITIP}$ | $g_{ITIP}$ |
| 9 | 28.3 | 25 | 0.5 | 0 |
| Related revenue, costs, and profit of ITIP | | | | |
| $R_{ITIP}$ | $RC_{ITIP}$ | $IC_{ITIP}$ | $TC_{ITIP}$ | Profit |
| $ 5,726.12 | $ 1,755.89 | $ 1,000.00 | $ 2,755.89 | $ 2,970.23 |

**Table II.2-4:** Optimal team design and results of ITIP

*Influence of the team size:* Based on our initial scenario and its optimal parameterization (see Table II.2-3 and Table II.2-4), we calculated the ITIP profit for diverging numbers of team members $P_{ITIP}$ in a range of 2 to 40 people, assuming that all other parameters remain constant (see Figure II.2-4). Regarding the influence of the team size $P_{ITIP}$, 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 ($P_{ITIP} \leq 4$), we can even observe decreasing profits with an increasing number of team members. This is due to the fact that the running costs $RC_{ITIP}$ increase more strongly than the additional revenue $R_{ITIP}$ resulting from a higher $NTM_P$. Teams of 5-8 people show an increasing profit with a growing number of team members, since the revenue $R_{ITIP}$ arising from a higher $NTM_P$ increases more strongly than the running costs $RC_{ITIP}$. 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 $RC_{ITIP}$ overcompensate the increase in revenue $R_{ITIP}$.The profit will be even negative for a high number of team members ($P_{ITIP} \geq 27$) since the high running costs $RC_{ITIP}$ exceed the revenue $R_{ITIP}$.

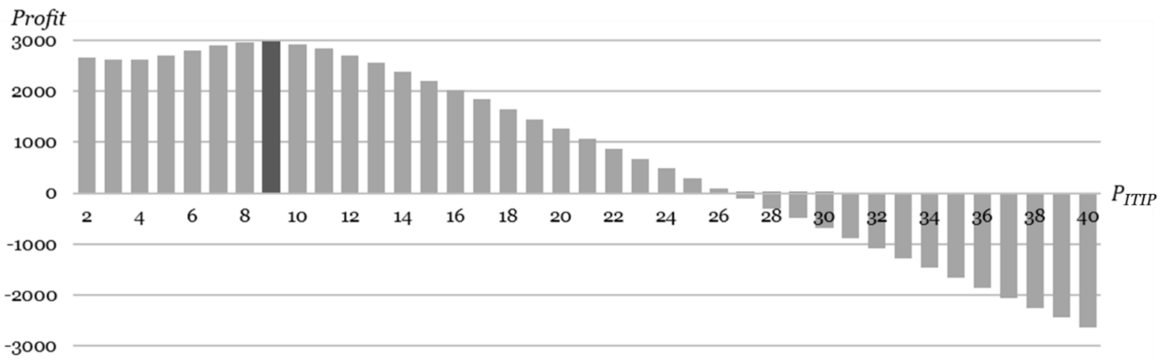


**Figure II.2-4:** Univariate sensitivity analysis for $\boldsymbol{P_{ITIP}}$

*Influence of the mean work experience:* In the next step, we calculated the ITIP profit for a mean work experience $w_{m_{ITIP}}$ in a range of 0 to 40, assuming that all other parameters remain constant (see Figure II.2-5). Regarding the influence of the team's mean work experience $w_{m_{ITIP}}$, 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.

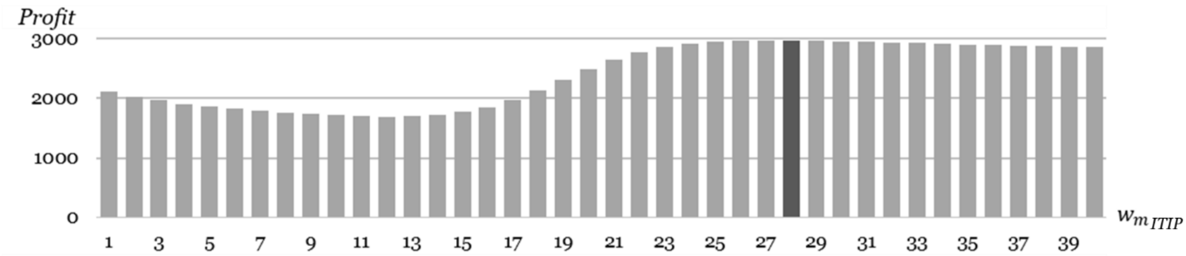


**Figure II.2-5:** Univariate sensitivity analysis for $\boldsymbol{w_{m_{IITP}}}$

*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 II.2-6). 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 $NTM_{w_d}$ that, in turn, leads to a higher $R_{ITIP}$ and a higher profit.

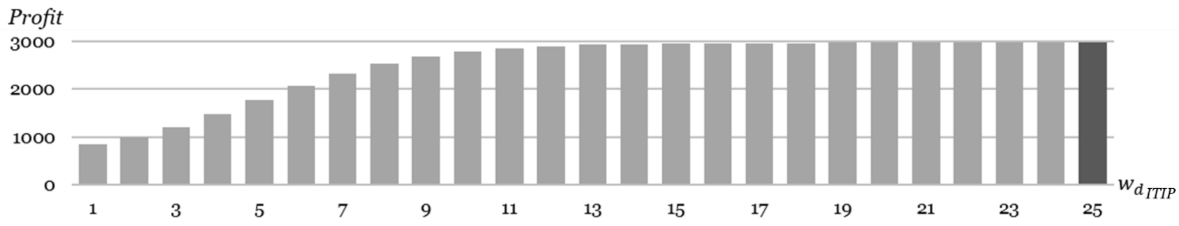


**Figure II.2-6:** Univariate sensitivity analysis for $\boldsymbol{w_{d_{ITIP}}}$

*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 II.2-7). 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.

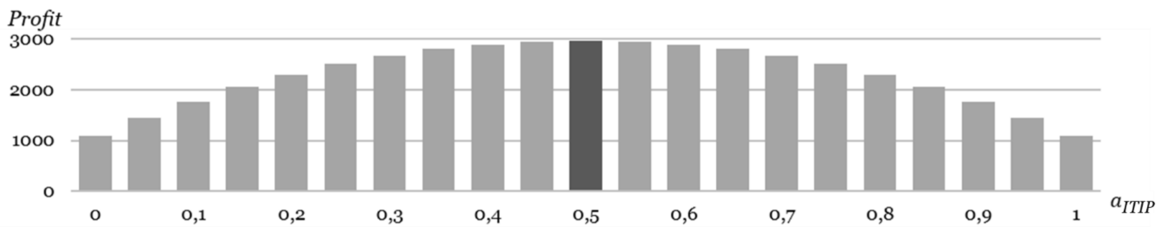


**Figure II.2-7:** Univariate sensitivity analysis for $\boldsymbol{a_{ITIP}}$

*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 II.2-8). As a result, we can observe that an increasing geographical diversity leads to a higher ITIP profit (for cases if $g_{ITIP} < 1$). 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 $IC_i = IC_{gi}$ (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 $IC_{gi}$ would be considerably higher than $IC_i$ (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).

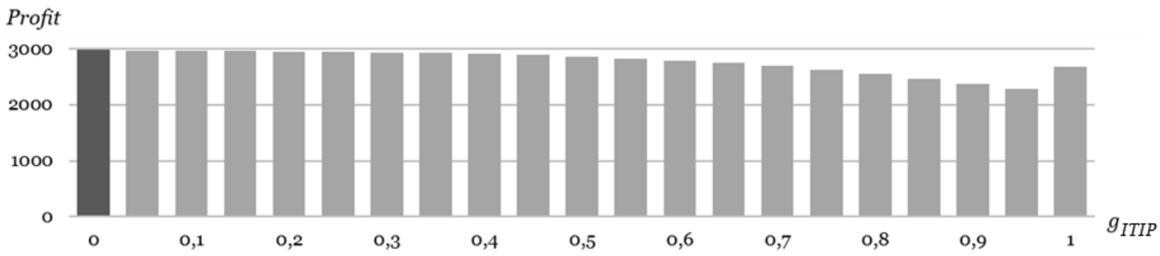


**Figure II.2-8:** Univariate sensitivity analysis for $\mathbf{g_{ITIP}}$

### *II.2.4.2 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 II.2-5 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 | $p_{ITIP}$ | $w_{m_{ITIP}}$ | $w_{d_{ITIP}}$ | $a_{ITIP}$ | $g_{ITIP}$ |
|---|---|---|---|---|---|
| Scenario 1 | {2;3;…;40} | (0 ; 50) | $(0\ ;\ \frac{w_{m_{ITIP}}}{2})$ | (0 ; 1] | (0 ; 1] |
| Scenario 2 | {6;7;…;11} | (20 ; 30) | $(0\ ;\ \frac{w_{m_{ITIP}}}{2})$ | (0.3 ; 0.8) | (0 ; 1] |

**Table II.2-5:** Data for the multivariate sensitivity analysis

Using the histogram resulting from the multivariate sensitivity analysis (see Figure II.2-9), 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.

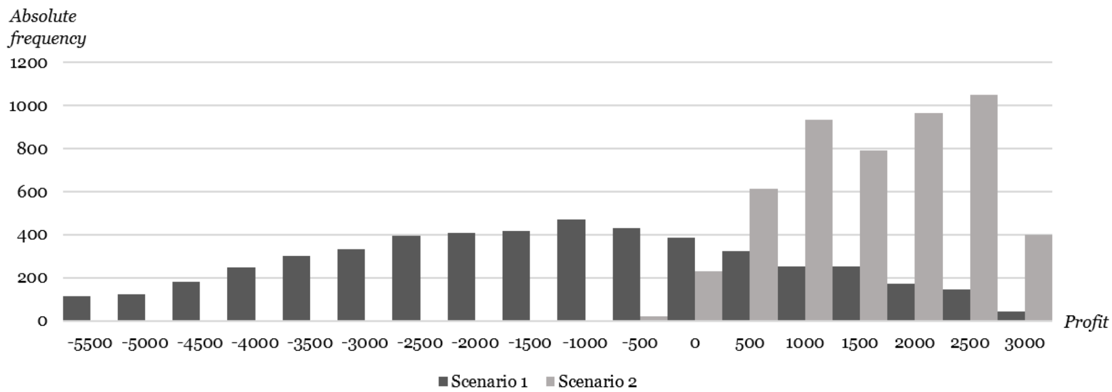


**Figure II.2-9:** Results for ITIP profit after multivariate sensitivity analysis

### *II.2.4.3 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 ($\vec{w}^{\,T} = (5,15,15,25,35)$), as well as an almost identical academic background ($a_{ITIP} =$

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) (see Table II.2-6). 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 II.2-3 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 II.2-6:** 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 II.2-4).
- 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 II.2-7). 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.

### II.2.5 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 analyze 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 analyze 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 analyzed 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 analyze 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 II.2-6. 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 analyze 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 Managing the Adoption of IT Innovations

This chapter focuses on managing the adoption of IT innovations. To remain competitive, companies need to systematically adopt IT innovations in their business activities and face thereby manifold challenges. First, companies need to balance their investment strategy with regard to risk and return potentials of IT innovations with different maturity by following the principles of VBM. Due to a high transformation potential of IT innovations, companies should also carefully plan and structure their adoption to ensure the value contribution of all adoption activities. Finally, they need to analyze the changes that may arise through adopting IT innovations, such as changes in the company's IT security risk landscape. Hence, this chapter includes three research papers that provide novel approaches dealing with these challenges to improve the management of IT innovation adoption.

The first research paper P3 "*Towards an Optimal Investment Strategy Considering Fashionable IT Innovations – a Dynamic Optimisation Model*" in Chapter III.1 develops a dynamic optimization model for determining the optimal allocation of strategic IT innovation budget to mature and fashionable IT innovations. Using a simulation-based approach, P3 analyzes the essential causal relationships between the theoretical optimum and the factors of major influence. By doing so, it provides an economic basis for investment decisions in IT innovations with different maturity.

The second research paper P4 "*How to Structure a Company-wide Adoption of Big Data Analytics*" in Chapter III.2 develops and evaluates a new method for structuring a company-wide adoption of BDA in a concerted research effort with a German bank. Based on the roadmapping approach, P4 illustrates how companies can define a target state, identify gaps, and derive a BDA roadmap to coordinate and prioritize the adoption measures, taking into account the dependencies in terms of content and time.

The third research paper P5 "*Value of Data meets IT Security – Assessing IT Security Risks in data-driven Value Chains*" in Chapter III.3 investigates the changes in the IT security risk landscape of manufacturing companies arising through the shift toward a data-driven value creation. P5 proposes a modeling approach for the assessment of IT security risks that helps companies to analyze data types in terms of value contribution and affiliated IT security risks and to protect their new data-based crown jewels in an appropriate way. P5 evaluates the new approach by means of interviews with industry experts and provides managerial implications.

# III.1 Research Paper 3: "Towards an Optimal Investment Strategy Considering Fashionable IT Innovations: a Dynamic Optimisation Model"[2]


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**Abstract:** *Companies regularly face the challenge of deciding whether, when and to which extent they should invest in information technology (IT) innovations with different maturity. The IT innovation strategy thereby should consider mature as well as fashionable IT innovations as investment alternatives. As previous research's focus is rather qualitative, we develop a dynamic optimisation model that determines the optimal strategic allocation of an IT innovation budget to mature and fashionable IT innovations. Using a simulation-based approach, we analyse the essential causal relationships between the theoretical optimum and the factors of major influence. We find that companies should invest in fashionable IT*

[2] Since this paper refers to work of Fridgen & Moser (2013), Häckel et al. 2013a, Häckel et al. 2013b, Häckel et al. 2016, Häckel et al. 2017, and Moser (2011), some statements might be similar or identical (especially in the model part or in the description of fashionable and mature IT innovations).

[3] The affiliation of Florian Moser has been updated because Mr. Moser changed his job after the publication of the paper.

*innovations even if their own level of innovativeness is rather low and the technology's success probability has not reached a high threshold yet. Our findings provide a basis for further research on mindful investment decisions in fashionable IT innovations.*

### III.1.1 Introduction

Due to the dynamic development of information technology (IT) as well as increasing competition and customer expectations, companies regularly face the challenge of deciding whether, when and to which extent emerging IT innovations should be adopted (Lu & Ramamurthy, 2010; Swanson & Ramiller, 2004). However, companies never know whether an emerging IT innovation will be the 'next big thing', that guarantees long-term success or whether there will be just a short-term hype that will sooner or later fade away, as was the case for the WAP technology or virtual worlds. Buzzwords like Internet of Things Platform, Affective Computing, Connected Home or Blockchain are some examples of IT innovations that have been hyped extensively by both, research and practice (Gartner, 2016). The list of new technologies not meeting the high expectations or the dotcom bubble should be a warning not to jump on the bandwagon and engage in IT innovations undergoing a transient hype phase just because of a gut feeling (Fenn & Raskino, 2008) and without thorough analysis. As IT innovations play a crucial role for many companies as to creating and sustaining a competitive advantage (Stratopoulos & Lim, 2010), a thorough analysis of possible investments in emerging technologies is crucial to generate the capabilities necessary to deal with IT innovation investments whose future development is highly uncertain (Fichman, 2004a; Lu & Ramamurthy, 2010).

To emphasise the peculiarities of such IT innovations undergoing a fashionable phase, literature agreed on a certain term for this type of IT innovation. In accordance with Wang (2010), Baskerville and Myers (2009), as well as Fichman (2004b), we define a fashionable IT innovation as an IT innovation that is undergoing a hyped phase. Mature IT innovations, by contrast, have already been widely accepted and institutionalised. Hence, IT fashion research examines the phase before a technology crosses the chasm from being a fashionable IT innovation to being a mature IT innovation (Moore, 2002; Van de Ven, 2005; Wang, 2010).

As IT innovations in general and fashionable IT innovations in particular often heavily affect the IT infrastructure, business processes and sometimes even the whole business model, investments in a losing technology can be a major threat to companies. This threat potential is amplified by a fashionable IT innovation's novelty and often revolutionary character as well as missing best practices (Fenn & Raskino, 2008). On the other hand, companies '[…] need a steady stream of IT experiments […]' to learn about the chances and limitations of new technologies (Ross & Beath, 2002). To guarantee sustainable learning and long-term competitive advantages and in order to keep a continual level of innovativeness, the IT strategy should consider both mature and fashionable IT innovations not merely as a flash in the pan but rather as a persistent share of its innovation strategy as often stressed in research (Dos Santos & Peffers, 1995; Hoppe, 2000; Stratopoulos & Lim, 2010). Even though the investment in fashionable IT innovations can yield higher returns than investments in mature IT innovations, which is due to competitive and first mover advantages, not all companies are able or willing to consider and manage the risks adequately. Therefore, some companies neglect a balanced view in the decision process (Lu & Ramamurthy, 2010; Swanson & Ramiller, 2004; Wang, 2010). In order to prevent decisions based on gut feeling, methodically rigour models that provide insights into the crucial determinants of IT innovation investment strategy are required.

Whereas at least a few papers in IT innovation research apply mathematical models (Williams, Dwivedi, Lal, & Schwarz, 2009), papers that consider fashionable IT innovations in a formal-deductive and mathematical model are – to the best of our knowledge – virtually absent. In this context, Williams et al. (2009) even demand more variety regarding the methodology in IT adoption and diffusion research to avoid overall homogeneity. Thus, our research questions are as follows:

RQ1. *What is a strategic IT innovation budget's optimal allocation to mature and fashionable IT innovations?*

RQ2. *How do company- and technology-specific factors influence the strategic IT innovation budget's allocation to mature and fashionable IT innovation investments?*

To investigate these research questions, we transfer the central findings and ideas of IT innovation, IT fashion and IT value theories to a formal-deductive mathematical model that enables an analytical approach towards the optimal IT innovation strategy considering fashionable IT innovations. We develop a dynamic optimisation model that addresses the idiosyncrasies of IT innovations compared to normal IT investments and determines the optimal strategic allocation of an IT innovation budget (ITIB) to two stylised types of IT innovation investments that differ regarding their maturity: mature IT innovations and fashionable IT innovations. Due to missing empirical data in this context, we follow Meredith, Raturi, Amoako-Gyampah, and Kaplan (1989) as well as Davis, Eisenhardt, and Bingham (2007) and apply a simulation-based approach. By conducting various sensitivity analyses as well as a Monte Carlo simulation we are able to analyse the crucial determinants and cause and effect relationships of our model. In particular, we investigate which company- and technology-specific influencing factors are the main drivers that determine whether a company adopts a rather conservative IT innovation strategy (i.e. primarily invests in mature IT innovations), or a rather offensive IT innovation strategy (i.e. primarily invests in fashionable IT innovations).

The paper is organised as follows: First, we give an overview of the relevant literature in IT innovation and IT fashion research. We also embed our paper in the large body of literature concerned with the valuation of IT investments in general, and investment strategies for IT innovations in particular. After that, we develop and analyse the model. Then we discuss the results, the utility and limitations of our model, and give an outlook on future research potential.

### III.1.2 Problem context and related work

In this section, we first provide an overview of IT innovation and IT fashion literature to sharpen our understanding of emerging IT innovations and to address their idiosyncrasies. Subsequently, we review the prior research on the business value of IT investments and embed our work in the large body of existing literature. Finally, we review approaches towards the evaluation of IT innovation investments and discuss influencing factors that should be considered. By discussing these aspects, we lay the theoretical foundation for our formal-deductive mathematical model, which we present in Section 3.

#### *III.1.2.1 IT innovation*

Swanson (1994) defines IT innovation as '[…] innovations in the organisational application of digital computer and communications technologies (now commonly known as information technology)'. The development of IT innovations follows a life cycle that is closely linked to the concept of technology adoption cycles, which were originally sketched by Rogers (2003) and extended into 'hype cycles' by the firm Gartner Inc. (Fenn & Raskino, 2008). Due to this concept, an IT innovation's life cycle starts by means of a *technology trigger* and excessive publicity leading to over-enthusiasm and investments based on bandwagon behaviour. The hype usually reaches a *peak of inflated expectations* before it fades away in a *trough of disillusionment*. Only few technologies are worth continuing experimenting with and putting in solid hard work in order to understand the technology's applicability, its risks, and its benefits leading to a *slope of enlightenment* for the technology, which is followed by a *plateau of productivity* (Fenn & Raskino, 2008).

Based on the life cycle described above, we define *fashionable IT innovations* as IT innovations that are in an evolutionary phase between technology trigger and trough of disillusionment (Fenn & Raskino, 2008; Wang, 2010). Though their long-term evolution is unclear and significant adoption is missing, they are accompanied by a hype through a fashion-setting network. The engagement in such innovations promises first mover and therefore competitive advantages in case that it becomes widely accepted and institutionalised. However, its immaturity makes estimations about a future evolution difficult as the hype might fade away before the IT innovation has reached a long-term productivity. Hence, apart from the technological risk that is associated with nearly every type of IT investment, investments in fashionable IT innovations are additionally associated with the risk of investing in a losing technology that will never be institutionalised.

In contrast, *mature IT innovations* are IT innovations that have already reached an evolution between the slope of enlightenment and the plateau of productivity (Fenn & Raskino, 2008) or, according to Roger's (2003) theory, have already been adopted by a significant share of the market. Despite institutionalisation, mass adoption has not been reached yet. Hence, on the one hand, their evolution can be estimated roughly and the risk of investing in a losing technology is comparatively smaller. On the other hand, early mover advantages cannot be realised anymore due to the already achieved level of market adoption. Examples of mature IT innovations that experienced a fashionable phase at an earlier stage are Customer Relationship Management, Enterprise Resource Planning, or Business Process Reengineering (Wang, 2010).

The discourse on IT innovations and their adoption are often accompanied by fashion waves (Abrahamson & Fairchild, 1999). However, the common IT innovation literature tends to neglect these idiosyncrasies. In order to explain why IT fashion research is a valuable contribution to (IT) innovation literature, we now give a short review on IT fashion literature.

#### *III.1.2.2 IT Fashion*

Similar to the organisational theory, where innovation research preceded IT innovation research, the IT fashion theory was developed from the general management fashion theory (Abrahamson, 1991). For the justification of separate IT fashion research, Fichman (2004b) and Wang (2010) offer arguments that distinguish management fashions from IT fashions even though – in practice – fashionable IT innovations often have administrative components and vice versa. In contrast to management fashions, IT fashions are often accompanied by high switching costs, which are caused by the restructuring of the IT infrastructure, or they have tangible artefacts like software and hardware. Additionally, management fashion skills often can be used in recurring scenarios and they can be abolished or superseded easily (Abrahamson, 1991; Wang, 2010), whereas fashionable IT innovation investments are often characterised by uniqueness due to various company-specific implementation details. In addition, Lee and Collar (2003) examine differences between IT fashions and management fashions concerning their life cycles. They find that, compared to management fashions, the ascent phase during which the hype around IT fashions grows is shortening faster over time meaning that IT fashions occur more frequently than management fashions what requires separate attention. Therefore, the uniqueness of IT innovations requires a separate fashion theory, which is specific to IT innovations as the latter imply a different kind of decision-making processes, different success drivers and different processes (Wang, 2010).

After discussing the terms IT innovation and IT fashion above, we in the following sections focus on the business value of IT investments in general (Section 2.3) and on evaluation approaches for IT innovations in particular (Section 2.4).

#### *III.1.2.3 Business value of IT investments*

The business value of IT investments has been discussed intensively in IS literature throughout the last decades. To investigate how, and to which extent IT investments contribute to firm performance, several business value models have been proposed (e.g. Dedrick, Gurbaxani, & Kraemer, 2003; Dehning & Richardson, 2002; Melville, Kraemer, & Gurbaxani, 2004). Although there is huge body of literature concerned with the business value of IT, its relevance is even increasing due to the crucial role of IT in the digital economy and the continuously increasing IT investment spending. Thus, companies are forced stronger than ever to evaluate IT investments mindfully with respect to the business value created (Mata, Fuerst, & Barney, 1995). Existing research on the business value of IT investment can be divided into studies that investigate the value of IT investments from an ex ante perspective and those that take an ex post perspective (Buhl, Häckel, Probst, & Schosser, 2016; Kohli & Grover, 2008). Whereas the ex post stream primarily investigates the extent to which IT investments have created value for the firm, the ex ante stream analyses which available IT investment alternatives best contribute to a company's business goals or preferences (Schryen, 2013). In our paper, we focus on the ex ante perspective as we aim at deriving a dynamic investment strategy for IT innovations with different maturity in order to support the decision-making processes of companies.

Although existing research provides various approaches for measuring the business value of IT investments, their comparison is rather difficult as the studies define IT as well as their value contribution very differently (Melville et al., 2004; Weill & Olson, 1989). Despite this challenge, there is a general agreement, that different types of IT investments require different evaluation approaches to consider their characteristics and associated influencing factors in an appropriate manner. For that reason, in our approach, we aim to capture the idiosyncrasies of IT innovation investments that might drive decision behaviour of companies. In particular, we take into account the dynamic development of IT innovations over time and thus, the high uncertainty about their expected payoffs.

To deal with the high uncertainty and temporal dynamics of IT investments in general, the prior research provides various approaches. In particular, the real option approach has received great attention in information systems literature over the last years (e.g. Benaroch & Kauffman, 1999; Fichman, Keil, & Tiwana, 2005; Ghosh & Li, 2013; Schwartz & Zozaya-Gorostiza, 2003; Taudes, Feurstein, & Mild, 2000). The real option approach is also widelyused to evaluate technology investments that are not necessarily related to IT. For example, McGrath (1997) argues that a company should invest in a technology option when the value of the underlying claim to commercialisation exceeds the price to create the option – the technology development costs. She further shows that companies can increase the value of a technology option through amplifying preinvestments. In this sense, collaborations can help to increase the sustainability of revenues by avoiding imitations of competitors and to decrease the commercialisation costs by setting a powerful standard and avoiding parallel technology development (Gans & Stern, 2003; McGrath, 1997). Van Mieghem (1998) uses a real option approach for analysing a multi-stage decision problem for optimal investment in flexible manufacturing capacity where a company has the option to invest in product-dedicated and flexible resources under demand uncertainty. However, some researchers challenge the appropriateness of the real option approach for the evaluation of IT investments. The criticism thereby is mainly focused on the restrictive assumptions resulting from the (pragmatic) application of financial option pricing theory (Bardhan, Bagchi, & Sougstad, 2004). Particularly, real option models rest on the assumption of complete markets and therefore, in particular assume that option payments are duplicable by an underlying traded instrument or another market instrument. However, insofar as IT investments are considered, project-specific risks are of paramount importance and thus, often impede the duplicability of cash flow effects (Buhl et al., 2016; Müller, Stöckl, Zimmermann, & Heinrich, 2016). As these obstacles hold true for the case of IT innovation investments even to a greater extent, we abstain from using an approach based on real option theory. Moreover, for answering our research questions a real option approach wouldn't be perfectly suitable, as we do not consider the typical case of evaluating a basic investment that enables options to expand or grow. Instead, we consider a dynamic budget allocation problem that focuses on the comparison between two different types of IT innovation investments.

Our dynamic optimisation approach thereby is based on the well-known net present value approach that is considerably less restrictive and thus applicable to the valuation of IT innovation investments (Irani, 2010; Irani & Love, 2002). Future net cash flows as a specific financial measure are often considered as a suitable approach to evaluate IT investments on a financial basis (e.g. Irani, 2010; Irani & Love, 2002; Renkema & Berghout, 1997). A central argument for the use of future net cash flows often cited in the literature is their direct relationship to the concept of value-based management, which aims to maximise the net present value of all future cash flows (Buhl et al., 2016). Another advantage of using future net cash flows is the fact that they take into account the time value of money and thus, in general support decision-making oriented to the long term (e.g. Renkema & Berghout, 1997). Furthermore, the net present value approach enables comparatively easy integration of risk, for example, by adjusting the discount rate according to the IT investment's specific risk (e.g. Verhoef, 2005).

Besides these arguments for using the net present value approach, literature emphasizes that such approaches have to take care of the specific characteristics of the IT investments under consideration (e.g. Anandarajan & Wen, 1999). Thus, within our dynamic optimization model we tailor the net present value approach to the idiosyncrasies of IT innovation investments and capture company-specific as well as technology-specific aspects.

In the following, we review approaches for evaluating IT innovation investments. By doing so, we aim at analysing the crucial peculiarities of IT innovations with different maturity and how the existent evaluation approaches consider them.

#### *III.1.2.4 Evaluation approaches for IT innovations with different maturity*

The importance of using IT innovations to gain a competitive advantage and to create longterm value for companies is unchallenged (Clark & Guy, 1998; Melville et al., 2004; Nadler & Tushman, 1999). However, especially decisions on investments in IT innovations in their early development phase (= fashionable IT innovations) are challenging due to a high uncertainty regarding their adoption and the strong influence of fashion waves (Fichman, 2003). To overcome this challenge, the optimal investment strategy should consider the idiosyncrasies of IT innovations with regard to their maturity. In this sense, Swanson and Ramiller (2004) and Fiol and O'Connor (2003) argue that companies should innovate mindfully, consider different types of IT innovations, and implement a well-founded decision process which incorporates the questions whether, when and to which extent new IT should be adopted.

To answer these questions, approaches to evaluate investments in IT innovations should also incorporate other IT innovation related issues (e.g. probability of institutionalisation, ability to innovate properly, impact of the technology) to depict the complexity of IT innovations more appropriately (Dewan & Mendelson, 1998; Fichman, 2004b; Rai, Brown, & Tang, 2009) and to integrate them into the decision calculus. Thereby, the ability to innovate properly and the extent of IT innovation adoption can be described as the innovator profile. Companies that fit this profile are expected to innovate more easily, more effectively and, consequently, more economically (Fichman, 2004a). The prevailing part of literature concerned with the innovator profile focuses on the question of how companies can become innovative by developing their innovator profile (Grover, Fiedler, & Teng, 1997; Iacovou, Benbasat, & Dexter, 1995) and how variables, such as a company's size, its structure or knowledge, affect the innovator profile. However, the question of how the innovator profile affects a company's investment strategy is widely unanswered.

Furthermore, prior studies regarding the evaluation of investments in (fashionable) IT innovations mostly focus on the timing aspect, i.e. when to invest in an IT innovation. For example, Dos Santos and Peffers (1995) demonstrate that the very early engagement in new IT can add over proportional value. In contrast, Hoppe (2000) shows that, under certain conditions, even second mover strategies can be advantageous due to spillover effects. Lu and Ramamurthy (2010) examine different strategies in stable and dynamic environments and show a general support for the assumption that proactive IT innovation leaders outperform reactive IT innovators as to the overall performance, allocation and cost efficiency. Wang (2010) finds that companies that invest in fashionable IT innovations gain a better reputation and improve their performance due to over proportional returns resulting from long-term competitive advantages. In the context of innovation persistence, Stratopoulos and Lim (2010) find that steady engagement in new emerging IT innovations is required for becoming a systematic innovator and those systematic innovators are more likely to outperform their competitors in the long run.

Quantitative approaches that comprehensively investigate the questions whether, when and to which extent new IT innovations should be adopted, are rather underrepresented in the prior research. Kauffman and Li (2005) apply a real options approach and argue that technology adopters are better off deferring investments until the technology's probability of becoming widely accepted reaches a critical threshold of ~60%. In practice, however, determining this point in time equals a herculean task. Häckel, Lindermeir, Moser, and Pfosser (2017) focus on the influence of organisational learning on the optimal IT innovation investment strategy and the resulting adjustment of budget allocation over a long-term planning horizon. Häckel, Lindermeir, Moser, and Pfosser (2016) also consider organisational learning and evaluate different IT innovation investment strategies from an ex ante and ex post perspective. However, both papers mainly focus on organisational learning but do not consider further impact factors that may drive the strategic allocation of a company's IT innovation budget.

Our literature review shows that there is a rich body of knowledge concerned with different facets of investments in IT innovations. However, there is a lack of comprehensive formal-deductive and mathematical models for the economic ex ante evaluation of investments in fashionable and mature IT innovations and a thorough analysis of crucial causal relationships that influence the investment strategy. Thus, drawing on related literature, we develop a dynamic optimisation model that determines the optimal strategic allocation of an IT innovation budget to mature and fashionable IT innovations. Our model further allows us to analyse the essential causal relationships between the theoretical optimum and the factors of major influence like the innovation characteristics (e.g. the probability of institutionalisation) and the company characteristics (e.g. the ability to innovate). Thus, our research aims on offering new insights into the crucial determinants of IT innovation investment strategy, and therefore, might provide a solid basis for companies to plan and improve their IT innovation investment activities.

### III.1.3 Towards an optimal IT innovation investment strategy considering fashionable technologies

#### *III.1.3.1 Research methodology*

To answer our stated research questions, we apply mathematical simulation as a special type of analytical modelling outlined by Meredith et al. (1989) as a common research method. Following this research paradigm (Meredith et al., 1989), we first develop a dynamic optimization model that aims at determining the optimal strategic allocation of a periodical IT innovation budget to mature and fashionable IT innovations. Although quantitative models usually simplify reality by concentrating on the crucial parameters, the analysis of a 'simplified' model regarding the optimal IT innovation budget allocation is still a rather complex problem.

To handle this complexity, we in a second step apply a simulation-based approach in order to identify and analyse important causal relationships between the optimal budget allocation and the parameters of major influence considered in our model. For that purpose, we describe a scenario in which a company is confronted with the problem of how to allocate a strategic IT innovation portfolio's budget to mature or fashionable IT innovation investments. Based on this scenario, we conduct different sensitivity analyses (simulating one parameter *ceteris paribus*) and a Monte Carlo simulation (simulating all parameters of major influence). As discussed by Meredith et al. (1989), Monte Carlo simulation is a legitimate way to analyse complex interrelationships. By doing so, we also follow the roadmap for developing knowledge and theory using simulation methods as outlined by Davis et al. (2007). In line with Davis et al. (2007, p. 481), we use the term theory as 'constructs linked together by propositions that have an underlying coherent logic and related assumptions'.

Some researchers challenge the appropriateness and the scientific value of simulation methods for theory development because of overly complex (Fichman, 1999) or inaccurate (Chattoe, 1998; Davis et al., 2007) results. According to our understanding, a simulation-based approach, used in an appropriate manner, allows for a comprehensive analysis of theoretical causal relationships with strong internal validity and the illustration of boundary conditions. However, in order to strengthen the external validity of our analysis and of the gained insight, further research regarding the evaluation of our model in a given organisational context might be useful (Wacker, 1998). For that purpose, we recommend empirical evaluation methods, such as case studies, field studies or statistical sampling, to test our approach (Hevner, March, Park, & Ram, 2004; Meredith et al., 1989; Wacker, 1998). This sequence of research activities is closely related to the basic idea of the research cycle of Meredith et al. (1989), who point out the importance of mathematical models providing first results, which can serve as the basis for future tests within empirical research. Hence, to address this issue and to outline next steps that should be considered in further research, Section 7 provides an explicit discussion on directions for future research regarding our optimisation approach, which should be addressed by means of additional evaluation methods.

#### *III.1.3.2 The model*

Our analysis' focus is on a company's IT innovation portfolio. At point of time $t = 0$ and $t = 1$, the company decides how it should allocate an initial strategic (i.e. not periodic but mid-term oriented) IT innovation budget (ITIB) to two different types of IT innovation investments (mature IT innovations vs. fashionable IT innovations) to maximise its cash flows. The investment opportunities are clustered in these two major categories according to their discourse, diffusion, popularity and maturity (Tsui, Wang, Fleischmann, Oard, & Sayeed, 2009; Wang, 2009).

The amount of the strategic IT innovation budget that is not allocated to mature or fashionable IT innovations in $t = 0$ is held back as strategic reserve to increase the investment budget at a later point of time. The strategic reserve is used when the company intends to defer an investment until more information about an IT innovation's development is available. The cash flows that result from the investments made in $t = 0$ are re-allocated in the same manner in $t = 1$ to generate cash flows in $t = 2$. Hence, the initial allocation in $t = 0$ significantly influences the investment capability in $t = 1$ and the cash flows in $t = 2$. Therefore, our model aims at determining the optimal strategic allocation of the company's initial IT innovation budget in $t$ = 0 and the optimal strategic allocation of the resulting cash flows in $t$ = 1 to maximise the cash flows in $t$ = 2 by means of a dynamic optimisation model. By that, an IT innovation's life cycle – as described in Section 2.1 – is broken down and modelled as a time frame including two periods, whereas $t$ = 0 describes the point of time when a fashionable IT innovation emerges and $t$ = 1 describes the point of time when its destiny turns out. Consequently, in case that a fashionable IT innovation becomes institutionalized (= mature), $t$ = 2 describes its plateau of productivity's altitude. In case of a mature IT innovation, the time frame illustrates its impact over two periods. Breaking an IT innovation's life cycle down into a time frame of two periods definitely simplifies the matter but, nevertheless, allows us to schematically model the idiosyncrasies of investment decision settings for fashionable IT innovations. In addition, limiting the model to two periods allows keeping the mathematical model as simple as possible while not limiting the central propositions for research and practice at the same time.

*III.1.3.3 Definitions and assumptions*

**Assumption 1:** *In* $t = 0$ *we assume an initial strategic IT innovation budget* $ITIB_0 > 0$ *that is provided to the IT innovation portfolio by the central IT budgeting planning as a strategic budget to work with over the planning horizon (Kiessling, Wilke, & Kolbe, 2011). No extra budget will be provided during the planning horizon so that* $ITIB_1$ *equals the cash flows that result in* $t = 1$. *We define* $a_t^i \in [0,1]$ *with* $i \in \{N, F\}$ *as the share of* $ITIB_t$ *that is invested in mature IT innovations (N) or fashionable IT innovations (F) in* $t = 0,1$. *Since companies naturally do not spend their whole IT innovation investment budget - due to a conservative investment strategy or the intention to defer an investment (Hoppe, 2000; Lu & Ramamurthy, 2010) - we define* $1 - a_t^N - a_t^F \geq 0$ *as the share of* $ITIB_t$ *that is held back as a strategic investment reserve R that allows to defer an investment until more information is available.*

Figure III.1-1 shows the split of $\text{ITIB}_0$ into the two investment alternatives $F$ and $N$ and the strategic investment reserve $R$, respectively. It also shows the cash flows that are realized in $t = 1$ (= $\text{ITIB}_1$). Those cash flows are re-allocated to $F$, $N$ and $R$ and generate cash flows in $t = 2$.

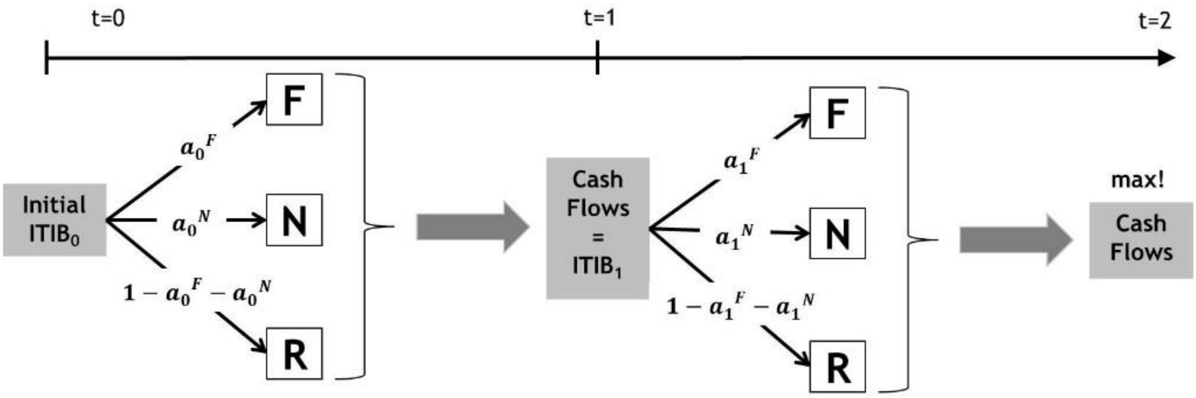


**Figure III.1-1:** The decision setting in $t$ = 0, 1, 2

*Assumption 2: The IT innovation portfolio's cash flow $CF_t^{PF}$ for $t = 1{,}2$ consists of the investments' cash flows $CF_t^F$ resulting from the investment in a fashionable IT innovation, $CF_t^N$ resulting from the investment in a mature IT innovation and $CF_t^R$ resulting from the liquidation of the strategic reserve and its interest payments. The strategic reserve's interest payment thereby can result from, for example, conventional investments in risk-free assets.*

$$CF_t^{PF} = CF_t^F + CF_t^N + CF_t^R \text{ with } t \in \{1{,}2\} \quad (1)$$

As a result of the initial investments in $t = 0$, the investments in *F* and *N* generate specific cash flows depending on the fashionable IT innovation's destiny and the mature IT innovation's success in the market. Additionally, the strategic reserve *R*, which was held back in $t = 0$, is available in $t = 1$ and - due to interest effects - generates capital gains and its own cash flow when liquidated. To model the idiosyncrasies of the decision setting in more detail, we take a closer look at the cash flows that are realized by *N*, *F* and *R*.

**Assumption 3:** *The cash flows $CF_t^F$, $CF_t^N$, and $CF_t^R$ in $t = 1{,}2$ depend on the IT innovation budget's amount that was allocated to F, N, and R in the previous period. For the sake of simplicity and easier interpretation, the cash flows in $t = 2$ are assumed to be perpetual and they can be interpreted as the cash flows that are realized with the IT innovation budget from $t = 2$ on (Copeland, Weston, & Shastri, 2005).*

**Assumption 4:** *The cash flows $CF_t^F$ and $CF_t^N$ resulting from the investments in F and N follow a strictly monotonically increasing, concave function, which is differentiable twice and depends on the IT innovation budget's share $a_{t-1}^i$ with $i \in [N, F]$ that was allocated to F and N in the previous period:*

$$CF_t^i(\ a_{t-1}^i) = \left(a_{t-1}^i \cdot ITIB_{t-1}\right)^{q_s^i} \cdot v \qquad (2)$$

with $q_s^i \epsilon\ [0,1),\ i \epsilon \{N, F\}\ , t \epsilon \{1,2\}\ , s \epsilon \{u, d\}, v \epsilon R^+$

A monotonically increasing cash flow function is reasonable due to the fact that a higher investment in and therefore commitment to an IT innovation generally makes a deeper engagement in and a broader implementation of the technology possible and therefore provides more opportunities to create value out of the investment (Fichman, 2004a; Kimberly, 1981; Melville et al., 2004). Furthermore, we can argue that an increasing investment in F or N is characterized by a diminishing marginal utility regarding $CF_t^i(a_{t-1}^i)$, i.e. $\partial^2(CF_t^i(a_{t-1}^i))/\partial^2 a_{t-1}^i < 0$, according to the production theory (Varian, 1999). Hence, a first engagement in IT innovation creates more value than the additional increase in an already quite high investment as companies need a reasonably high initial engagement to enter a market or become reasonably familiar with a technology (Lu & Ramamurthy, 2010; Stratopoulos & Lim, 2010). Moreover, research on organizational learning in the context of IT innovations usually assumes a so-called s-curve (logistic function) in order to describe the development of the innovator profile over time (Häckel et al., 2017). This s-curve depicts the increasing but somehow limited ability to innovate with IT. Taking into account such a diminishing marginal effect of organizational learning also supports the assumption of a diminishing marginal utility and thus, a concave cash flow function. In line with literature, a concave cash flow function ensures that a pure "more is better"-approach might not hold true for every IT innovation investment. This is also reflected in our model, since it is possible that the invested share of the budget $a_{t-1}^i \cdot ITIB$ exceeds the resulting cash flows $CF_t^i(a_{t-1}^i)$ because of diminishing marginal utility. This would lead to a loss for the company.

The factor $q_s^i$ with $i \epsilon \{N, F\}$ and $s \epsilon \{u, d\}$ that is constant over time can be interpreted as a technology-specific impact factor describing the impact degree of N and F, i.e. its general acceptance by customers or employees, its stability, or the probability of an easy integration into the existing IT infrastructure of companies, that influences the investment's cash flow (Fichman, 2004a; Haner, 2002). As fashionable IT innovations, in case they are institutionalized and accepted by the market, usually have a higher impact and therefore generate higher cash flows for the company - due to the first mover advantage, possible new business models, and positive interactions with the existing infrastructure (Lu & Ramamurthy, 2010; Wang, 2010) - we assume F's technology-specific impact factor $q_s^F$ with $s \epsilon \{u, d\}$ to be generally higher than N's $q_s^N$ with $s \epsilon \{u, d\}$, i.e. $q_s^F > q_s^N \forall\, t = 1{,}2\ with\ s \epsilon \{u, d\}$. However, as an IT innovation's impact on the market is difficult to predict, we model an upside scenario (with $s = u$) as well as a downside scenario (with $s = d$) for N and F into the technology-specific impact factor, i.e. $q_u^i > q_d^i \forall\, t = 1{,}2$ with $i \epsilon \{N, F\}$ and incorporate uncertainty about the IT innovation's possible outcome (Fenn & Raskino, 2008). An upside scenario regarding an IT innovation can be interpreted, for example, as high acceptance by customers or employees or easy integration into existing infrastructure, thereby leading to higher cash flows or institutionalization in the first place (especially in the case of fashionable IT innovations). A downside scenario can be characterized, for example, by difficulties with the integration into existing processes or even the case of the IT innovation getting stranded (in the case of fashionable IT innovations). Therefore, cases where the mature IT innovation might have a higher impact in a positive scenario than the fashionable IT innovation might have in a negative scenario, i.e. $q_d^F < q_u^N$, are possible. Although modeling only "positive" or "negative" scenarios leads to a rather binary view and simplifies real world scenarios that might lie somewhere in between, this approach/methodology incorporates the borderline cases which are of high relevance for this analysis.

The constant factor $v \epsilon R^+$ can be interpreted as the company's individual innovator profile indicator describing its ability to engage in an IT innovation economically, quickly and efficiently (Fichman, 2004b; Swanson & Ramiller, 2004). As companies that innovate steadily have more experience in integrating new IT into an existing infrastructure, making employees adopt the new technology and using an IT innovation to create products that are accepted by customers, we assume those companies to have a higher innovator profile indicator (Stratopoulos & Lim, 2010). To enable an easier interpretation of the innovator profile $v$, we level a company that is on average or opportunistically innovative with $v^* \epsilon R^+$, non-innovators with $v < v^*$, and innovators, i.e. first and progressive movers, with $v > v^*$ in order to transfer empirical findings by Stratopoulos and Lim (2010) as well as Lu and Ramamurthy (2010) to an analytical model.

To sum up, both factors, the technology-specific impact factor $q_s^i$ with $i \epsilon \{N, F\}$ and $s \epsilon \{u, d\}$ and the company's individual innovator profile indicator $v \epsilon R^+$ consolidate a variety of different factors. Certainly, these factors can be split up into several sub-dimensions that might be addressed in further research. However, as we focus on a more general level in order to keep the balance between rigorousness and interpretability, a simplification of the reality is reasonable in this case.

***Assumption 5:*** *Uncertainty about the mature and fashionable IT innovation's possible outcome (i.e. which of the scenarios $q_u^i$ or $q_d^i$ with $i \epsilon \{N, F\}$ occurs) and thereby the risk of undesirable outcomes is described by the probability $p^i$ for upside scenarios (with $q_u^i$) and $(1 - p^i)$ for downside scenarios (with $q_d^i$) with $i \epsilon \{N, F\}$ via a binomial distribution. The probabilities $p^i$ with $i \epsilon \{N, F\}$ are assumed to be constant over time as the uncertainty about the future development can - in this very early phase of the adoption lifecycle - be assumed as almost equally high.*

Hence, $p^i$ with $i \epsilon \{N, F\}$ describes the possibility that an investment in N creates the desired cash flows ($N^u$ with $q_u^N$) in $t = 1{,}2$ or, in case of F, becomes institutionalized (if at all) in $t = 1$ and creates desirable cash flows in $t = 2$ ($F^u$ with $q_u^F$). By means of $1 - p^i$ with $i \epsilon \{N, F\}$ we describe the probability that an investment in *N* will create below-average cash flows ($N^d$ with $q_d^N$) in $t = 1{,}2$ or, in case of F, will turn out to be a losing technology in $t = 1$. In case that *F* becomes institutionalized in $t = 1$, $1 - p^F$ represents the probability that *F* will create below-average cash flows in $t = 2$ ($F^d$ with $q_d^F$). Figure III.1-2 illustrates the different scenarios that can occur regarding the development of *F* and *N* and the probabilities for the scenarios. It becomes clear that in case that *F* gets stranded in $t = 1$ (leading to zero cash flows), the company will only depend on the cash flows resulting from *N* in $t = 1{,}2$.

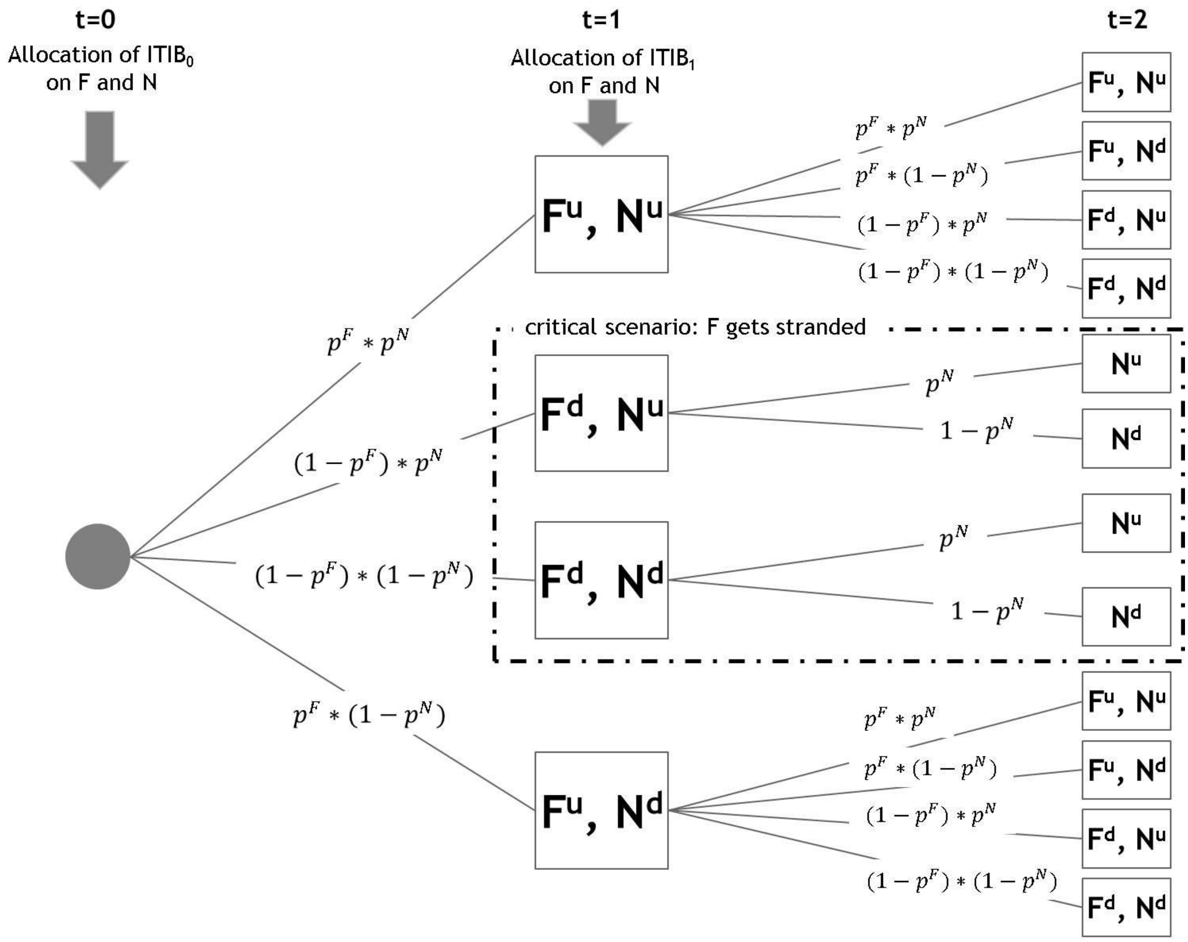


**Figure III.1-2:** The scenarios for the development of the IT innovations *F* and *N* in *t* = 0, 1, 2

**Assumption 6:** *The company is a risk-neutral decision maker that aims at maximizing the net present value (NPV) of the IT innovation portfolio's expected cash flows* $E(CF_t^{PF})$ *with* $t = 1{,}2$. *The expected cash flows are discounted to present with a risk-free interest rate* $r \epsilon [0{,}1]$ *that is assumed to be constant for each period.*

Assuming the decision maker deciding on a company's IT innovation portfolio to be risk-neutral is reasonable as the IT innovation portfolio's scope is to fund basic research to discover and realize long-term value propositions. Hence, an IT innovation portfolio, by definition, deals with riskier investments than, for example, an IT asset portfolio, which deals with infrastructure, operational data and routine processes (Maizlish & Handler, 2005; Ross & Beath, 2002). Table III.1-1 summarizes the most crucial parameters of the model.

| Description | Parameter |
|---|---|
| Initial strategic IT innovation budget | $ITIB_0$ |
| Share of $ITIB_t$ that is invested in fashionable IT innovations in t | $a_t^F$ |

| | |
|---|---|
| Share of $ITIB_t$ that is invested in mature IT innovations in t | $a_t^N$ |
| Company's individual innovator profile indicator | v |
| Fashionable IT innovation's impact factor in case of high market impact | $q_u^F$ |
| Fashionable IT innovation's impact factor in case of low market impact | $q_d^F$ |
| Mature IT innovation's impact factor in case of high market impact | $q_u^N$ |
| Mature IT innovation's impact factor in case of low market impact | $q_d^N$ |
| Probability that fashionable IT innovation will create desirable cash flows | $p^F$ |
| Probability that mature IT innovation will create desirable cash flows | $p^N$ |

**Table III.1-1:** Summary of the most crucial parameters

### *III.1.3.4 Cash flows in t*

The IT innovation portfolio PF in $t$ realizes cash flows resulting from the investments in $F$, $N$ and $R$, respectively. According to our assumptions, investing in a fashionable IT innovation $F$ or a mature IT innovation $N$ in $t-1$ can result in the following cash flows $CF_t^F$ or $CF_t^N$ with $t = 1{,}2$:

| | | $t = 1$ | $t = 2$ |
|---|---|---|---|
| Upside scenario ($p^i$ ) with $i \epsilon \{N, F\}$ | F | $(a_0^F * ITIB_0)^{q_u^F} * v$ | $(a_1^F * ITIB_1)^{q_u^F} * v$ |
| | N | $(a_0^N * ITIB_0)^{q_u^N} * v$ | $(a_1^N * ITIB_1)^{q_u^N} * v$ |
| Downside scenario ($1 - p^i$ ) with $i \epsilon \{N, F\}$ | F | 0 | $(a_1^F * ITIB_1)^{q_d^F} * v$ |
| | N | $(a_0^N * ITIB_0)^{q_d^N} * v$ | $(a_1^N * ITIB_1)^{q_d^N} * v$ |

**Table III.1-2:** Scenarios for the IT innovation's cash flow

As it is easier to make predictions about the future impact of certain technologies in later periods, the company may hold back a strategic reserve in $t = 0{,}1$ to be able to defer IT innovation investments. The cash flow $CF_t^R$ resulting from the liquidation of the strategic reserve held back in $t-1$ and its interest payments has the following form for $t = 1{,}2$:

$$CF_t^R(a_{t-1}^N, a_{t-1}^F) = (1 - a_{t-1}^N - a_{t-1}^F) * ITIB_{t-1} * (1 + r) \tag{3}$$

The cash flow $CF_1^{PF} = CF_1^F + CF_1^N + CF_1^R$ that results from the allocation of the initial strategic IT innovation budget in $t = 0$ ($ITIB_0$) is the basis for further investments (=$ITIB_1$) in $t = 1$:

$$ITIB_1 = CF_1^F(a_0^F) + CF_1^N(a_0^N) + CF_1^R(a_0^F, a_0^N) \tag{4}$$

After describing the particular decision-making problem, possible scenarios, and cash flow outcomes for $t = 1{,}2$, we in the following present the objective function and analyze the model.

#### *III.1.3.5 Objective function*

The company allocates an initial IT innovation budget $\mathrm{ITIB}_0$ in $t = 0$ to *F*, *N* and *R* generating cash flows in $t = 1$. The cash flows realized in $t = 1$ are re-allocated to *F*, *N* and *R* and thus generate further cash flows in $t = 2$ which are to be maximized. Thus, we aim at maximizing the IT innovation portfolio's expected net present value (NPV), which depends on the cash flows expected in $t = 1$ and $t = 2$. As we assume the cash flows expected in $t = 2$ to be perpetual, i.e. they are realized with the IT innovation portfolio from $t = 2$ on, we maximize the expected NPV of the IT innovation portfolio's allocation of $\mathrm{ITIB}_0$ and $\mathrm{ITIB}_1$to *F*, *N* and *R*. Hence, the objective function is of the following form:

$$\max_{a_0^F, a_0^N, a_1^F, a_1^N} -\mathrm{ITIB}_0 + \frac{E\left(CF_1^{PF}\right)}{1+r} + \frac{E\left(CF_2^{PF}\right)}{r*(1+r)} \quad s.t. \tag{5}$$

$$0 \le a_t^i \le 1 \quad \forall t = 0{,}1;\ \forall\, i \in \{N, F\}$$

$$0 \le a_t^F + a_t^N \le 1 \quad \forall t = 0{,}1$$

$$\mathrm{ITIB_t} = CF_t^{PF}(a_{t-1}^F, a_{t-1}^N) \text{ with } t = 1$$

### III.1.4 Model analysis

To solve this dynamic optimisation problem, we use a roll-back approach on the basis of the decision tree that is determined by the scenarios described in Figure III.1-2. We analyse the tree with the different scenarios regarding the evolution of *F* an *N* and conduct a roll-back (i.e. dynamic programming according to Bellman (Bellmann, 1957)) analysis (Clemons & Weber, 1990; Magee, 1964; Suleyman, 1993). Subsequently, the company repeats the optimization and possibly re-allocates its ITIB in accordance with the realised scenarios or when new information is available. A major advantage of this decision tree-based roll-back analysis is that its primary focus is on the decisions that must be made relative to an investment, and the incorporation of interrelationships between variables. Additionally, it not only incorporates interrelationships but even optimises over the possible decisions (Bonini, 1975). A real options approach, as applied by Kauffman and Li (2005) or Fichman (2004a), might also be suitable to address this decision setting but inherits restrictive assumptions, such as the existence of a twin security, and therefore is not suitable for an ex ante allocation of an ITIB.

At this point it is almost impossible to obtain real world data to examine the benefits of our theoretic approach profoundly as companies often lack thorough decision setting approaches.

However, as stated in the subsequent sections, considerable advantages can be realized by incorporating the results obtained by means of the model in strategic decisions on whether, when and to which extent a company should allocate an IT innovation budget to mature and fashionable IT innovations. Due to the lack of empirical data, we apply a simulation-based approach to analyze our model as outlined by Meredith et al. (1989) and Davis et al. (2007). To derive first results, we analyze some of the most crucial model parameters (uncertainty, company's individual innovator profile, technology-specific impact factor) and discuss their influence on the optimal allocation. For each parameter, we first conduct a sensitivity analysis and analyze a small number of scenarios by slightly changing the values of the parameters (within their full range) ceteris paribus. In this way, changes in the model's output can be "[…] apportioned to different sources of uncertainty in the model input." (Saltelli, Ratto, Andres, Campolongo, Cariboni, Gatelli, Saisana, & Tarantola, 2008). In a subsequent Monte Carlo simulation, we generate 1,000 different investment settings for each analysis and vary the probabilities $p^F$ and $p^N$, the company's individual innovator profile $v$ and $p^F$ as well as the technology-specific impact factors $q_u^F$ and $q_u^N$ pairwise and randomly. Finally, to derive results and hypotheses in a more general setting, we conduct a Monte Carlo simulation with random changes of *all* parameters of major influence. As our analysis shows that the results change only slightly with an increasing number of investment settings, which - on the other hand - increase the runtime of the simulation rapidly, we choose 1,000 investment settings.

Table III.1-3 shows the initial values, their ranges and distributions. The initial values are held constant within the sensitivity analysis and the pairwise simulation (except for those parameters that are subject to the further analysis). Their ranges and distributions are relevant to the simulation. The values in the table serve as starting points for each analysis that follows. For the sake of simplicity we speak of $v$, $q_s^i$ and $p^i$ with $i \epsilon \{F, N\}$ and $s \epsilon \{u, d\}$ in the subsequent sections and assume equal distributions as other distributions, such as the Gaussian, would not distort the general conclusions but increase complexity. Analogous to Kauffman and Li (2005) we assume $r = 0.1$ for the risk-free interest rate $r$. We generally start our analysis with rather conservative values and also let the relevant parameters range in conservative intervals to avoid distortion due to overoptimistic value estimations. Although our analysis includes the determination of the optimal values for $t = 0,1$, we (due to space restrictions) focus on the ex ante analysis in $t = 0$ for the optimal allocation to fashionable IT innovations and use a limited number of simulations and parameters. As already mentioned above, our focus is to illustrate and analyze causal relationships that influence the strategic IT innovation budget allocation rather than to provide specific guidelines or recommendations for choosing concrete IT innovations. Therefore, the measurement or estimation of the input factors of our model to suit real-world decision settings is not in the scope of our paper.

| Parameter | Initial Value | Range |
|---|---|---|
| Company's individual innovator profile indicator v | 100 ($= v^*$) | 70 - 130 |
| Fashionable IT innovation's impact factor $q_u^F$ (upside scenario) | 0.5 | 0.20 - 0.50 |
| Fashionable IT innovation's impact factor $q_d^F$ (downside scenario) | 0.3 | 0.05 - 0.30 |
| Mature IT innovation's impact factor $q_u^N$ (upside scenario) | 0.35 | 0.10 - 0.35 |
| Mature IT innovation's impact factor $q_d^N$ (downside scenario) | 0.2 | 0.01 - 0.20 |
| Probability that fashionable IT innovation will create desirable cash flows $p^F$ | 0.05 | 0.05 - 0.15 |
| Probability that mature IT innovation will create desirable cash flows $p^N$ | 0.4 | 0.20 - 0.40 |

**Table III.1-3:** Data for sensitivity analysis and Monte Carlo simulation

### *III.1.4.1 Influence of uncertainty*

As a result of the sensitivity analysis we can state that, according to our model and parameterization, there is a generally positive relationship between the probability $p^F$ and the optimal share $a_0^{F^*}$ in fashionable IT innovations. In case of scenarios with low $p^F$, it is striking that even a slight increase in $p^F$ leads to a steep increase in $a_0^{F^*}$. Thus - under certain circumstances - companies should invest a significant amount (~48%) of their IT innovation budget in fashionable IT innovations even though the probability that high cash flows will be created is not higher than 15% (see Figure III.1-3). Unsurprisingly, there is a negative relation between $p^N$ and $a_0^{F^*}$, since mature IT innovations become more attractive as $p^N$ increases. However, even in the (unrealistic) case that mature IT innovations ensure desirable cash flows ($p^N = 1$), companies should invest at least a small amount of their budget in fashionable IT innovations (see Figure III.1-4).

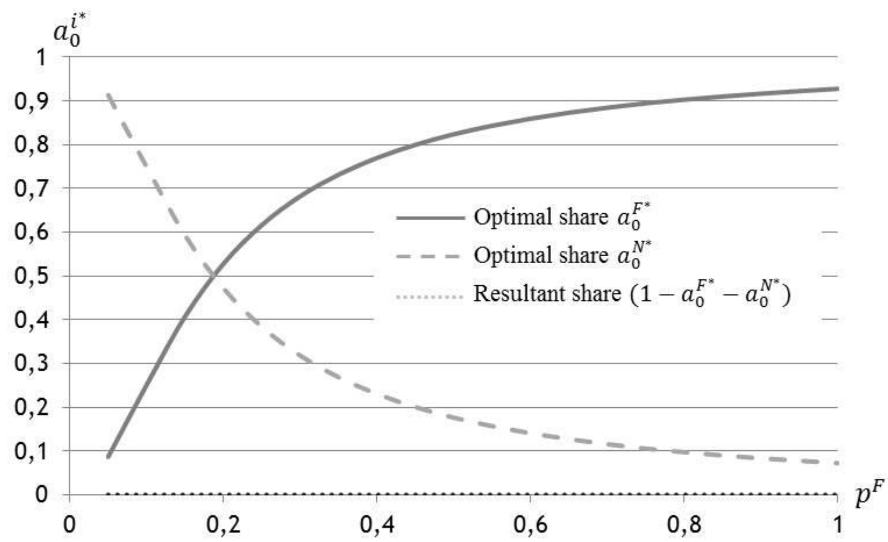


**Figure III.1-3:** Optimal allocation of $ITIB_0$ to $F$, $N$ and $R$ in $t$ = 0 relative to $\boldsymbol{p^F}$

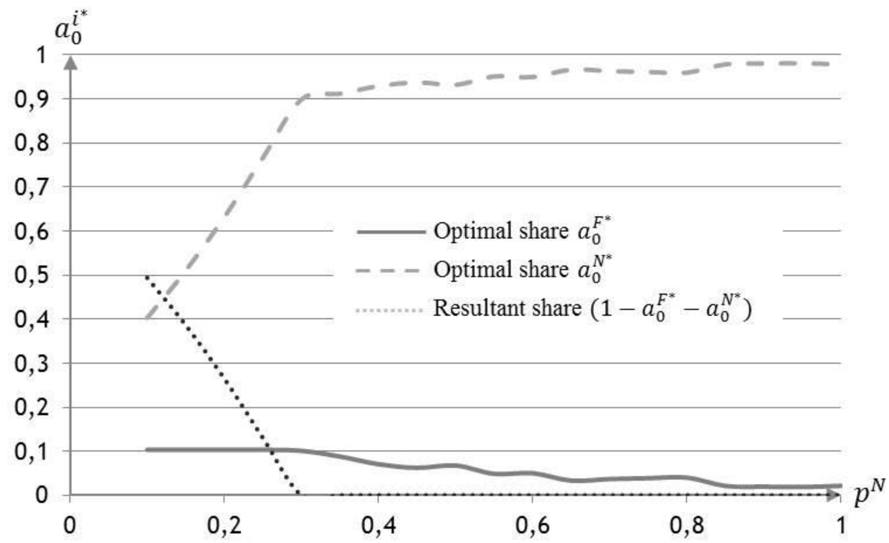


**Figure III.1-4:** Optimal allocation of $ITIB_0$ to $F$, $N$ and $R$ in $t$ = 0 relative to $\boldsymbol{p^N}$

The conducted Monte Carlo simulation regarding $p^N$ and $p^F$ supports these result as $a_0^{F^*}$ ranges from 8.82% to 55.16%, pointing out uncertainty's major influence on the optimal share structure. The minimum allocation of 8.82% and the mean allocation of 30.18% to fashionable IT innovations even strengthen the fact that it is advisable to significantly engage in fashionable IT innovations in an early phase even if the success probability is very low (~5% in case of the minimum allocation) (see Figure III.1-5).

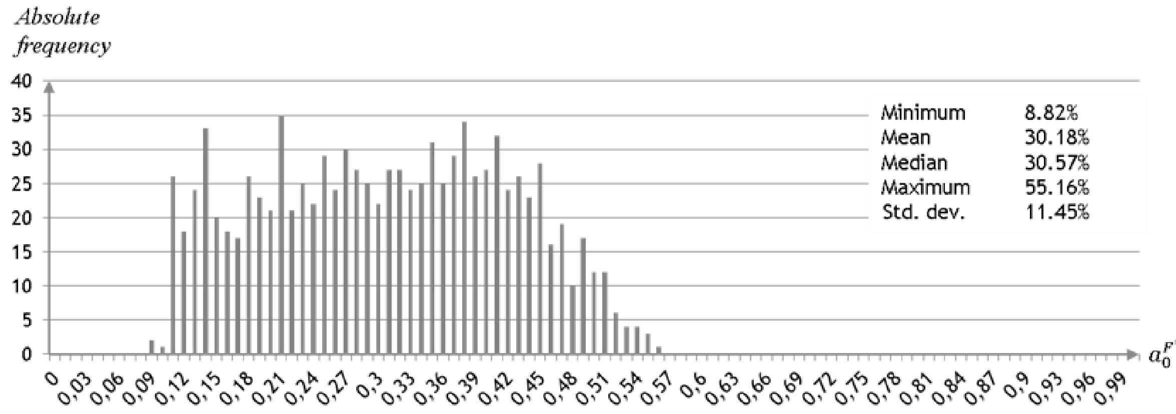


**Figure III.1-5:** Results for $\boldsymbol{a_0^{F^*}}$ after Monte Carlo simulation regarding $\boldsymbol{p^N}$ and $\boldsymbol{p^F}$

All in all, we have shown that the probabilities $p^F$ and $p^N$ have a major influence on the optimal allocation. Furthermore, we hypothesize that companies should invest at least a small amount of their IT innovation budget in fashionable IT innovations even though their success probability might be rather small.

### *III.1.4.2 Influence of the company's individual innovator profile*

Regarding the influence of the company's individual innovator profile $v$ we can conclude that, according to our model and parameterization, companies should invest in fashionable IT innovations almost independently of their innovativeness. Moreover, companies with $v < v^*$should invest a slightly lower amount in fashionable IT innovations and allocate more to the strategic reserve to defer investments in later periods when more information about the possible outcome is available. Furthermore, we can show that $a_0^{F^*}$ is near-constant for companies with $v > v^*$ (see Figure III.1-6).

The Monte Carlo simulation regarding $v$ and $p^F$points out that companies should allocate at least a small part of their initial ITIB (5.96%) to fashionable IT innovations even if their level of innovativeness is well below the average ($v{\sim}74$) and the possibility of creating desirable cash flows by means of a fashionable IT innovation is very low ($p^F{\sim}5.1\%$) (see Figure III.1-7). Furthermore, it could be beneficial to an innovative company ($v{\sim}128$) to allocate a significant part (40.74%) of its initial ITIB to fashionable IT innovations even if the maximal probability of success ($p^F$) in the simulation is 15%.

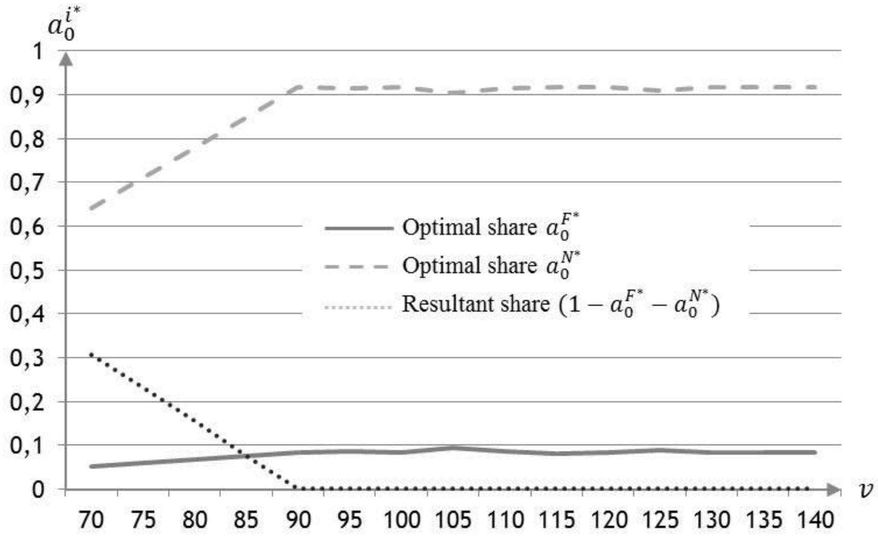


**Figure III.1-6:** Optimal allocation of ITIB$_0$ to *F*, *N* and *R* in *t* = 0 relative to $\boldsymbol{v}$

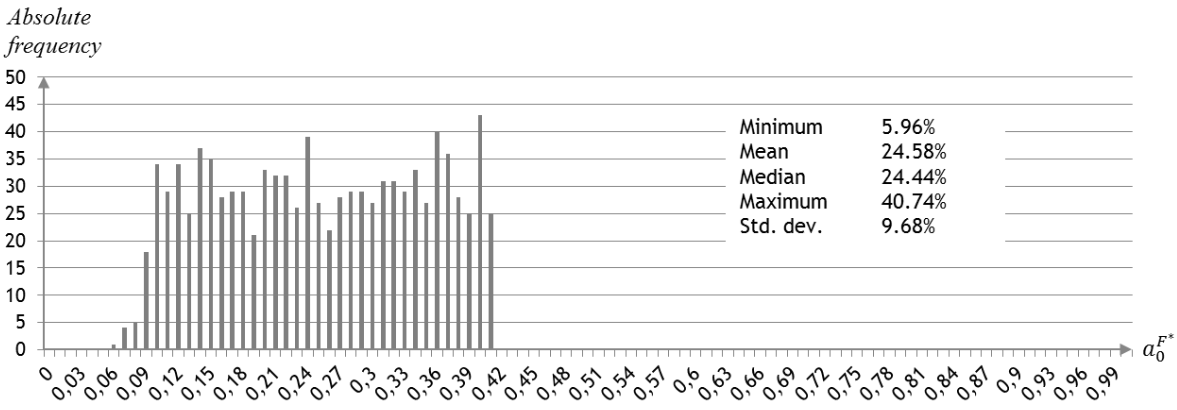


**Figure III.1-7:** Results for $\boldsymbol{a_0^{F^*}}$ after Monte Carlo simulation regarding $\boldsymbol{v}$ and $\boldsymbol{p^F}$

Based on our analysis, we hypothesize that companies are better off investing significantly in fashionable IT innovations instead of avoiding them, even if their level of innovativeness is below average. As, according to our model, the company's individual innovator profile obviously has a high impact, the appropriate parametrization is crucial for the validity of the results of the strategic budget allocation. Nevertheless, as our focus is to depict and analyze essential causal relationships, we assume the company's individual innovator profile to be known and do not discuss possible methods for measuring this parameter in real-world settings.

### *III.1.4.3 Influence of technology-specific impact factors*

We find a generally positive relationship between $q_u^F$ and $a_0^{F^*}$. Nevertheless, only a significant increase in $q_u^F$ leads to a significant increase in $a_0^{F^*}$. Thus, companies should only allocate a large amount of their IT innovation budget to fashionable IT innovations in case of a rather high $q_u^F$ (see Figure III.1-8). Unsurprisingly, there is a slightly negative relation between $q_u^N$ and $a_0^{F^*}$, since mature IT innovations create higher cash flows as $q_u^N$ increases (see Figure III.1-9). However, even in the extreme case of a higher impact of the mature IT innovation, where $a_0^{F^*}$ tends towards zero (i.e. $q_u^N > q_u^F$ with $q_u^F = 0.5$ as initial value), companies should invest a very small amount in fashionable IT innovations (see Figure III.1-9).

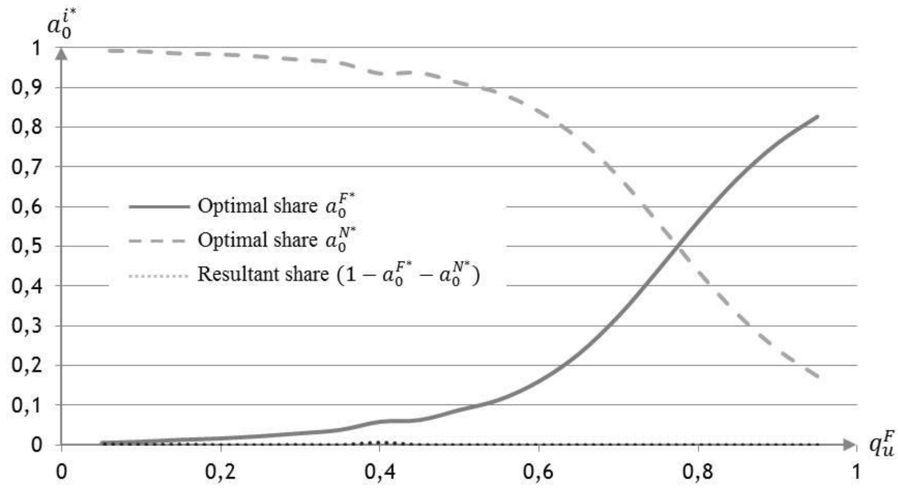


**Figure III.1-8:** Optimal allocation of ITIB$_0$ to *F*, *N* and *R* in *t* = 0 relative to $\boldsymbol{q_u^F}$

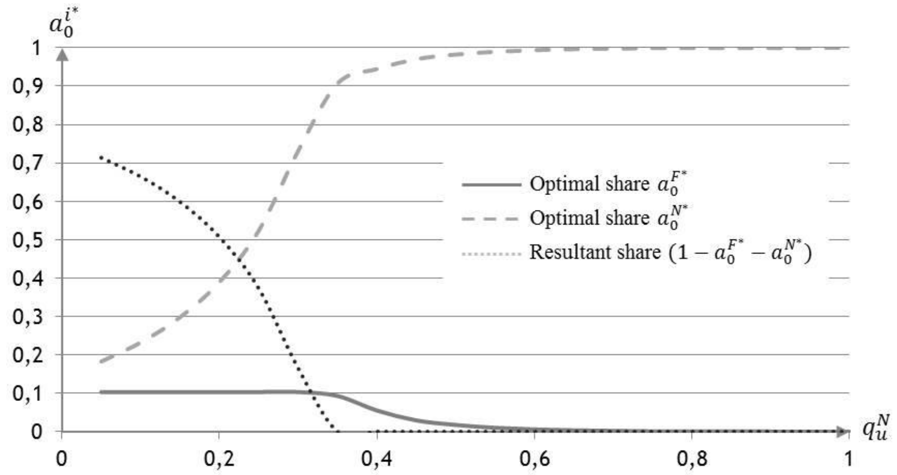


**Figure III.1-9:** Optimal allocation of ITIB$_0$ to *F*, *N* and *R* in *t* = 0 relative to $\boldsymbol{q_u^N}$

A Monte Carlo simulation regarding $q_u^F$ and $q_u^N$ strengthens this result as $a_0^{F^*}$ranges between 1.78% and 10.30% (see Figure III.1-10) and provides results with a surprisingly low standard deviation (2.26%). However, compared to the other simulations, the mean allocation is rather low (4.60%). This can be explained by the fact that in this simulation the success probability of the fashionable IT innovation remains constantly low with $p^F = 0.05$ (see Table III.1-3).

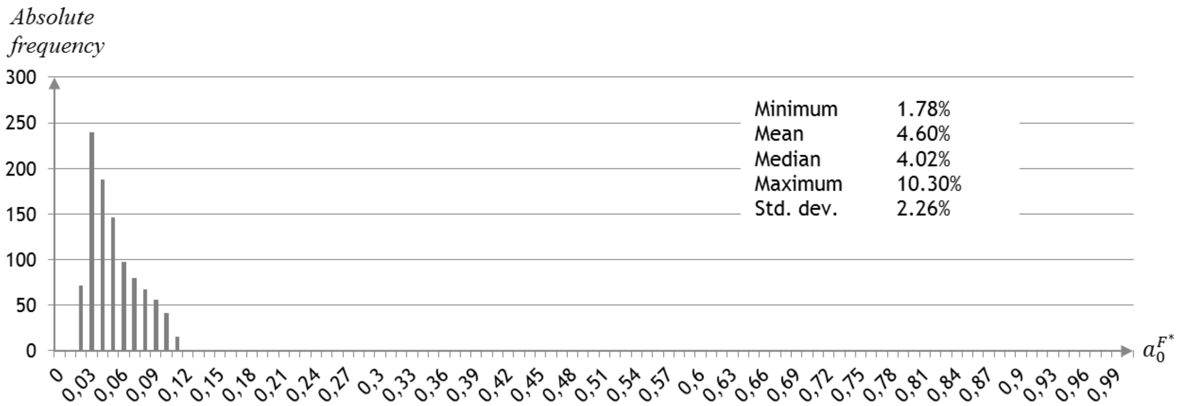


**Figure III.1-10:** Results for $\boldsymbol{a_0^{F^*}}$ after Monte Carlo simulation regarding $\boldsymbol{q_u^F}$ and $\boldsymbol{q_u^N}$

To sum up, we hypothesize that companies achieve a higher expected NPV for their IT innovation portfolio by significantly allocating a strategic IT innovation budget to fashionable IT innovations whose impact factor is relatively high.

#### *III.1.4.4 Simulation of all parameters*

Simulating all parameters has supported the other results, so far. Due to the large number of possible constellations regarding the influencing parameters, $a_0^{F^*}$ ranges from 1.60% to 75.45%. Interestingly and counter intuitively, it can be stated that even in the extreme case of low values for $p^F$ (5.34%), $q_u^F < q_u^N$, and - simultaneously - a below-average level of innovativeness $(v \sim 75)$, the company is better off investing a small amount (1.60%) in fashionable IT innovations (see Figure III.1-11). To sum up, we can state that under the conditions of simulating all parameters, companies should on average invest about 14.46% of their IT innovation budget in fashionable IT innovations – a significant amount of the initial ITIB.

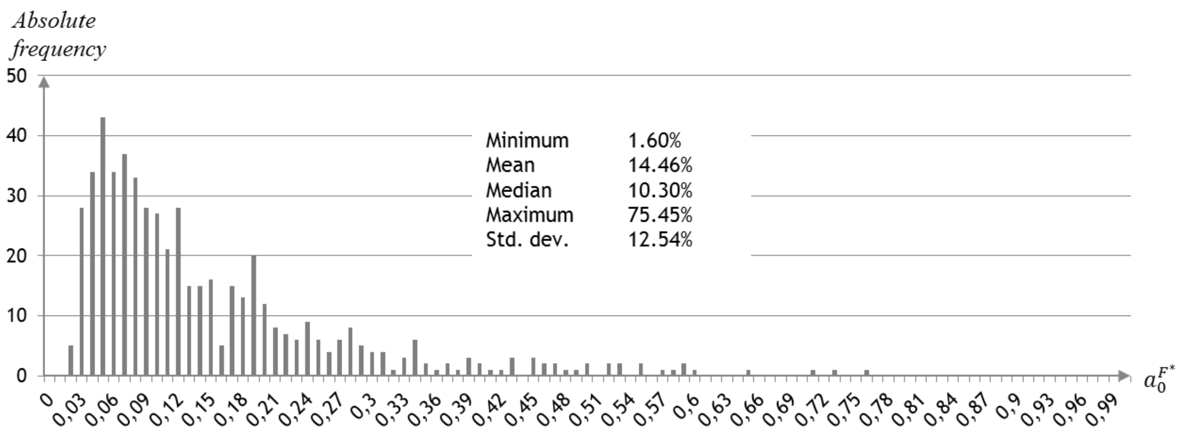


**Figure III.1-11:** Results for $\boldsymbol{a_0^{F^*}}$ after Monte Carlo simulation regarding $\boldsymbol{q_u^F, q_d^F, q_u^N, q_d^N, p^F, p^N, v}$

### III.1.5 Discussion of the results

Although different model settings, simplifying assumptions or model-specific parameters limit comparisons between different research approaches, it is worth discussing our results with regard to previous research to emphasise the need for future research and to identify contrary or supportive arguments. In our paper, we consider a scenario in which the company is confronted with the challenge to allocate a strategic IT innovation portfolio's budget to mature or fashionable IT innovation investments. Thereby, we consider investments in fashionable IT innovations to be those, which aim at breakthrough innovations and find that a mean allocation of 14% of the strategic ITIB to fashionable IT innovations is optimal. Our findings are comparable with those of Nagji and Tuff (2012) who find that the most innovative companies in the technological sector usually allocate about 15% of their innovation portfolio spending to transformational innovations that aim at breakthrough technologies. It also is comparable with the findings of Ross and Beath (2002), who empirically analyse the allocation of IT budgets to IT experiments in different industries. They examine ranges from 3 to 15% – values that are similar to those of our analysis as we generally expect our results to be slightly decreased in reality due to conservative decision-makers. Our results also support previous empirical findings of Wang (2010), who states that an engagement in fashionable IT innovations provides the opportunity to create long-term success. He empirically demonstrates that companies investing in fashionable IT innovations perform worse in the short term (after one year) but show a higher performance after three years (2010). An optimal investment strategy with a significant share of investments in fashionable IT innovations – as presented in our model – also supports the findings of Stratopoulos and Lim (2010), who emphasise the companies' need for persistent consideration of emerging IT innovations. They find that companies do not become innovative through ad hoc investments in IT innovations but only through a significant and steady stream of engagement in emerging technologies. By stating that an investment strategy with a significant share of investments in fashionable IT innovations in a very early phase (i.e. $t = 0$) is beneficial, our findings are also comparable with those of Dos Santos and Pfeffers (1995). They claim that an early adopter strategy can increase the firm's value. The results regarding the role of the technology-specific impact factor and the individual company's innovator profile are in accordance with Fichman (2004a), who emphasises that factors such as technological dominance or the capability to innovate influence the advantageousness of investments in immature technologies and provide a platform for later investments. In general, our findings are in accordance with those of Lu and Ramamurthy (2010), who find that proactive IT leaders outperform reactive IT leaders. We extend earlier findings by Kauffman and Li (2005), who – in a similar context – suggest adopting a new technology only if its probability to become institutionalized is greater than 60%. We find that an early investment strategy, i.e. a mean allocation of about 30% of the ITIB to fashionable IT innovations, makes sense even if the probability is considerably lower than 60% (see also Figure III.1-5). However, our findings support their line of considering uncertainty and success probability adequately.

This brief discussion makes clear that further research is required to examine further aspects within this research area and it explains why more mathematically oriented research in combination with empirical testing might provide valuable insights into the crucial determinants of IT innovation investment strategy regarding IT innovations with different maturity. In the following, we discuss the utility of our model as well as theoretical and practical implications. Thereafter, we discuss limitations of our approach, and aspects worth examining in future research.

### III.1.6 Utility of the model, theoretical and practical implications

Regarding decisions on investments in IT innovations that are undergoing a hyped phase (= fashionable IT innovations), companies often jump on the bandwagon instead of making a well-founded decision. To ensure mindfulness in determining an appropriate IT innovation investment strategy, our paper aims at supporting companies in allocating their ITIB to IT innovations with different maturity. In particular, we investigate which company- and technology-specific factors mainly influence companies in choosing a rather conservative or offensive IT innovation investment strategy.

Due to missing formal-deductive and mathematical research regarding this topic, we develop an optimisation model that allows us to analyse the crucial causal relationships between the innovation characteristics (e.g. the probability of institutionalisation), the company characteristics (e.g. the ability to innovate), and the optimal strategic allocation of an ITIB to fashionable and mature IT innovations. By considering both fashionable and mature IT innovations, our approach incorporates a portfolio perspective and theoretically shows that there is an optimal investment strategy with regard to these two investment types. Furthermore, we take a dynamic perspective as we determine the optimal allocation of the

ITIB at different points in time by considering possible scenarios or new information. Moreover, our approach covers both, specifics of fashionable and mature IT innovations, such as their uncertainty and their technology-specific impact factor, as well as company characteristics, such as the company's individual innovator profile. Depending on these parameters and their interrelationship, the allocation of the ITIB to fashionable IT innovations should be increased or decreased. By means of our dynamic optimisation approach, we address one central question of the IT innovation theory: whether, when, and to which extent should a company innovate with IT (Swanson & Ramiller, 2004). Our approach allows us to derive the following implications for research and practice to answer the stated research questions and to contribute to previous literature:

- Companies should invest in fashionable IT innovations even though their success probability has not reached a high threshold [*whether?*]
- Significant investments in fashionable IT innovations in very early phases are beneficial, even though a company's level of innovativeness and the technology's success probability might be rather low [*when?*]
- Companies are well-advised to incorporate a technology's prospective impact and related success probability in the decision calculus [*to which extent?*]

Following Kauffman and Li (2005), our model aims at '[…] an analogy between the technical details of the decision model and the exigencies of its application in an appropriate managerial context' (2005). Despite the fact that our model depicts reality in a slightly constrained way, the results of our ex ante optimisation model are comparable with those of previous qualitative and empirical literature. Thus, our model complements previous literature by covering and analysing the essential causal relationships that influence a company's IT innovation investment strategy. Moreover, our model provides a solid base for the future development of decision models that focus on the selection of concrete IT innovations from a set of possible technologies. Certainly, the specific design of our dynamic optimization approach and the underlying assumptions lead to results, which in some cases deviate from the findings of previous research. However, our results offer new insight into the crucial determinants of a company's IT innovation investment strategy, and thus, provide guidance for companies to plan and improve their IT innovation investment strategy related to fashionable and mature technologies. Next to its benefits for business practice, our study serves as the basis for further analytical research on IT innovation investment strategy and contributes to the understanding and improvement of this research stream.

### III.1.7 Limitations and future research

Our model supports the human decision-maker by determining the optimal engagement in IT innovations with different maturity based on a theoretically well-founded set of causal relationships. Thus, our model might help to prevent decisions purely on gut feeling. However, the human decision-maker still plays an essential part in determining the innovation-specific and company-specific input parameters of the optimisation problem (e.g. the estimation of a fashionable IT innovation's chances of success). Therefore, the experience and market assessment of decision-makers are still crucial for deriving a reasonable investment strategy.

Further, companies (i.e. the decision-makers) usually should consider each IT innovation individually and then mindfully decide whether it is appropriate to invest, and how the innovation could be managed to achieve the best results. Consequently, determining the optimal strategic budget allocation on IT innovations with different maturity by considering crucial causal relationships is only the first part of the IT innovation decision process. In the next step, decision-makers need to operationalise the fundamental investment strategy by evaluating and selecting concrete IT innovations. Thus, further research is required to address these aspects and to support companies in the selection process to find the 'right' IT innovations.

To incorporate our optimisation model into real-world decision-making processes, a company needs to estimate precise or at least approximate values for the model's input parameters. In this context, they can consider assessments through experts or consultants based on experience from former investments, or by benchmark analyses within the market. Whereas some factors are rather company-specific and need to be estimated by each company, others are technology- or market-specific and do not differ for different companies. Further testing of the approach using different model settings of previous studies in order to analyse differences and similarities of the results should also be done in future research. Furthermore, empirical testing of the model and its parameters – e.g. the different dimensions of an IT innovation's impact factor or a company's innovator profile – using real-world data should be done in further research. Some aspects that have not yet been covered or that need further methodological effort are the incorporation of switching costs, spillover effects, uncertainty, n-period analyses or learning aspects. In particular, when further developing our approach to a long-term oriented, n-period model it could be a promising idea to include the worst-case scenario that the company can go bankrupt. In an n-period model, bankruptcy could originate either from investing considerable amounts in a losing technology or, from the fact that the company gets outpaced by competitors due a too conservative or wrong investment strategy. Modelling such a scenario, it could also be a worthwhile research endeavour to assume a risk averse decision-maker. As future returns are irrelevant in case of bankruptcy and thus, the company wants to prevent such a worst-case scenario under all circumstances, assuming risk aversion might offer additional insights into the decision behaviour of companies. Furthermore, it has to be mentioned that the model's inherent interpretation of the IT innovation's value is rather abstract, i.e. our model is limited to deal with quantifiable and attributable components of value. We also do not consider that a technology might require a minimum engagement and we do not differentiate between different fashionable IT innovations. Thus, as various technologies might develop differently, modelling different fashionable IT innovations with varying details regarding the technological impact factor, success probability, etc. might provide additional insight. Furthermore, we did not evaluate, whether our model is appropriate for every company that wants to invest in IT innovations. Obviously, there are different internal and external factors that can influence a company's IT innovation strategy. For example, factors like company size (e.g. large company versus SME), the role of IT (e.g. IT as a core business versus IT as infrastructure), the considered sector (e.g. manufacturer versus service provider), or the business environment (dynamic versus stable) should be considered in future research to evaluate the appropriateness of our model for a concrete company. Our model most likely will be more appropriate for a high-tech company like Google, where IT is the core business and which competes in IT innovations in a highly dynamic environment rather than for a low-tech company, where IT is only a part of the infrastructure. However, the pervasive digitalization and the massive growth of the internet of things increasingly also force low-tech companies and manufactures into an IT innovation race, implying the need to engage in fashionable IT innovations. Therefore, our model can also be beneficial for a low-tech company confronted with the challenges of digitalisation.

Despite these limitations, our model presents a theoretically sound, economic approach, which allows further development and provides insight into IT innovation related issues. Hence, the presented paper serves as a basis for future analytical research on fashionable IT innovations and therefore contributes to the understanding of and improvement in this research stream as '[…] IS researchers should be among the leaders, and not just the followers, of fashion'. (Baskerville & Myers, 2009)

### III.1.8 Disclosure statement

No potential conflict of interest was reported by the authors.

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## III.2 Research Paper 4: "How to Structure a Company-wide Adoption of Big Data Analytics"

| | |
|---|---|
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**Abstract:** *Driven by increasing amounts of data and by emerging technologies to store and analyze them, companies adopt Big Data Analytics (BDA) to improve their innovativeness and decision-making. However, adopting BDA across the company in the sense of an insight-driven organization (IDO) is challenging, since it influences the entire company and requires an organizational change. Despite mature knowledge, approaches that provide concrete methods for structuring the company-wide adoption of BDA to fully exploit the benefits of BDA and to reduce the risk of its failure are still missing. Following action design research, we developed and evaluated a method for structuring the company-wide adoption of BDA in a concerted research effort at a German bank. Based on knowledge of BDA and the roadmapping approach, the method structures the adoption along the BDA capabilities. We illustrate how companies can define a target state, identify gaps, and derive a BDA roadmap.*

### III.2.1 Introduction

Inspired by big players, such as Google and Amazon, companies increasingly adopt Big Data Analytics (BDA) as an approach to utilize big data and advanced analytics for delivering value, improving efficiency, and establishing competitive advantage [1], [2]. The rapid growth of data generated by social media like Facebook and Twitter, as well as emerging information technologies (IT) like the Internet of Things, advance this trend [2], [3]. Additionally, the market increasingly offers more mature and powerful tools to source, store, and analyze big data, which lay the foundation for adopting BDA. Considering its technological capabilities and the associated high expectations, it is not surprising that BDA is – meanwhile – considered as a game changer, due to its operational and strategic potential [1]. Thereby, adopting BDA across the whole company instead of only using it within individual projects is considered as more beneficial since companies that use BDA as a competitive differentiator, – defined as insight-driven organizations (IDOs), – tend to perform better in terms of financial and operational results [4], [5]. They are champions in implementing BDA and improving the speed and quality of action through data-driven decisions [4], [5].

However, a company-wide adoption of BDA is challenging as it requires a long-term evolution [3], involves different stakeholder groups, impacts various levels of the enterprise architecture, and needs high investment amounts [6]. Due to this complexity, a structuring approach is important to coordinate the individual measures, taking into account the dependencies in terms of content and time. Prior research has already revealed factors that may be relevant for a structured adoption of BDA. For example, [7] address the need for a clear vision of what companies want to achieve and a roadmap to reach the target. [4] concretize that companies should define the business challenges, identify the organizational changes needed, and derive a roadmap. However, they do not show how companies can apply this procedure. Furthermore, prior studies recommend the development of BDA maturity or capability models that allow companies to assess their current state regarding the required capabilities [8]. However, they fail to illustrate how these models can be used for a coordinated company-wide adoption of BDA. Finally, [5], [9] advise companies to start with seed or lighthouse projects for a few use cases to gain initial experience with BDA, encourage collaboration, and create awareness. Thereby, they do not consider the long-term changes. Thus, despite addressing important issues, approaches that provide concrete methods for structuring the company-wide adoption of BDA are still missing. In order to contribute to this research gap, we study the following research question: *How can developing a roadmap assist in structuring the company-wide adoption of BDA?*

In order to answer this question, we adopt action design research (ADR) and develop a method that aims to assist companies in structuring a company-wide adoption of BDA. In line with ADR, we develop and evaluate our method in a concerted research effort at a German bank [10]. The paper is organized as follows: Section 2 contains a brief overview of the related research. After introducing our methodology in Section 3, we describe our method's design in Section 4 and evaluate it in Section 5. We conclude by discussing implications, limitations, and directions for future research in Section 6.

## III.2.2 Background and Related Work

Since our research is motivated by a concrete problem in practice, we have first discussed their needs with the end-users to achieve an in-depth understanding of the problem, and then researched the literature for appropriate methods to solve it. Therefore, this section provides a brief overview of the work related to BDA as the main content of the project and to roadmapping as one possible concept to approach the solution of the problem. As already recommended by prior research (e.g. [4], [7]), we focus on roadmapping to structure the adoption of BDA since it allows to define a target state, to identify gaps, and to derive and prioritize measures to reach the target state.

### *III.2.2.1 Big Data Analytics (BDA)*

Prior research states that developing appropriate BDA capabilities can help companies to successfully adopt BDA in order to become an IDO. Thereby, studies define different BDA capabilities. For example, [11] identify culture, data management, and skills as the main dimensions of a BDA capability, whereas [1] define BDA infrastructure, personnel, and management capability as the key components. [8] identify thirty four generic capabilities, which they assign to eight capability fields (e.g. customer relationship management, strategy development, and transformation competence). Thereby, they state that the relevance of the capabilities might vary, depending on the scenario. Despite differences about the identified components and the level of granularity, all studies have a multidimensional perspective and address the need to develop BDA capabilities to successfully adopt BDA. Further, [4] provide an approach that could be the first step toward a BDA maturity model. They consider people, processes, and tools as the necessary building blocks for BDA and define three levels of BDA capability: aspirational, experienced, and transformed. Whereas aspirational organizations focus on process efficiency or process automation to cut costs, experienced organizations aim at optimizing their organizations by developing new ways to use BDA. Transformed organizations (i.e. IDOs) focus on using BDA as a competitive differentiator to expand their market position [4]. During the transformation, BDA expands from use in only selected business units toward organization-wide adoption [4], [9]. Further studies highlight the need for managing transformation effectively [5] and structuring it by defining a clear vision, identifying required changes, and deriving a roadmap to achieve the target state [4], [7]. Since the company-wide adoption of BDA might require a long-term evolution, companies can start with lighthouse projects for selected business units to gain initial experience with BDA [5], [9] and provide initial results by using prototyping.

#### *III.2.2.2 Roadmapping*

The roadmapping approach is a widely used management concept for supporting strategy and innovation [12]. It has been widely adopted at various levels of granularity from product to industry sector and also across various industries [6], [12]. Thereby, roadmaps can be used to communicate visions, to explore the development of the business and its components, to coordinate activities and resources, and to monitor progress [12], [13]. They also enable the alignment of different functions and perspectives within an organization, particularly business and technology [12]. The roadmaps are also very flexible and scalable, and can be customized to suit different strategic and innovation contexts [14]. The most general approach delivers a framework that addresses three key questions: 1) Where do we want to go? 2) Where are we now?, and 3) How can we get there? [12]. The first key question refers to the definition required for a target vision, the second one aims at covering the gaps between the status quo and the target vision, and the third one includes identifying, as well as structuring, the measures for achieving the target vision. The roadmap architecture consists of two dimensions: 1) timeframes, as well as 2) layers and sub-layers [12]. Timeframes are usually the horizontal axis and include short-, medium-, and long-term perspectives, as well as the past and vision. The layers and sub-layers are usually the vertical axis and show different levels of a hierarchical taxonomy. Since roadmaps can be used at various levels of granularity, the roadmap architecture should be customized to suit the aims and scope of the contemplated effort [12].

### III.2.3 Research Method

In order to answer our research question, we relied on Action Design Research (ADR) to build, intervene, and evaluate our method. ADR involves the construction of an artefact, its intervention in the organization, and its evaluation by means of a concerted effort [10]. The developed artefact reflects, therefore, not only the theoretical precursors and the researchers' intent, but also the users' influence in organizational contexts [10]. Using ADR enabled us to design and fine-tune our method such that we could provide both academic insights and practical value. We implemented the four ADR stages. According to the first stage, – problem formulation, – we studied the research gap in the existing knowledge and outlined our research question in the introduction [10]. The second stage involves building, intervention, and evaluation activities. During this stage, we designed and evaluated our method at a German bank. In the third stage, – reflection and learning, – we continuously reflected on our method's design and analyzed the intervention results in context of our method's goals by integrating the feedback received from practitioners and end-users. In the fourth and last ADR stage that aims to formalize the learning gained throughout the project, we identified general insights about activities and techniques (cf. introducing our method below).

<table>
<tr><th></th><th>Name</th><th>Description</th></tr>
<tr><td rowspan="4">Attributes</td><td>(A.1) Goal orientation</td><td>Methods must strive for achieving specific goals</td></tr>
<tr><td>(A.2) Systematic approach</td><td>Methods must include a systematic procedure model</td></tr>
<tr><td>(A.3) Principles orientation</td><td>Methods must follow general design guidelines and strategies</td></tr>
<tr><td>(A.4) Repeatability</td><td>Methods must be repeatable in different contexts</td></tr>
<tr><td rowspan="5">Elements</td><td>(E.1) Activity</td><td>Task that creates a distinct (intermediate) output</td></tr>
<tr><td>(E.2) Technique</td><td>Detailed instruction that supports the execution of an activity</td></tr>
<tr><td>(E.3) Tool</td><td>Tool (e.g. method) that supports the application of a technique</td></tr>
<tr><td>(E.4) Role</td><td>Actor that executes or is involved in the execution of an activity</td></tr>
<tr><td>(E.5) Defined output</td><td>Defined outcome per activity (e.g. artefact, documents)</td></tr>
</table>

**Table III.2-1:** Mandatory method components [15]

In order to ensure that our method includes the relevant attributes and elements needed to design a new method, we further relied on the mandatory method components provided by [15] as shown in Table III.2-1.

## III.2.4 The Method Design

### *III.2.4.1 Design Principles*

In line with ADR, we derive design principles for our method [16] from the existing theory and knowledge gained during the project [10]. As detailed above, a company-wide adoption of BDA is challenging as it affects various levels of the enterprise architecture and involves different stakeholder groups [6]. Thus, the company-wide adoption of BDA needs a clear vision of the target state, as well as a concept to capture the status quo, and to identify the changes needed to reach the target [4], [5], [7]. Thereby, a BDA capability model can provide guidance on which capabilities an organization should develop to become an IDO [4], [8]. This leads us to define the following design principle: *(DP.1) The method should allow for a precisely defined target state to be achieved by the adoption of BDA and identification of measures to close the gaps between the status quo and the target state. It should further take into account BDA capabilities needed as well as various levels of the enterprise architecture and stakeholder groups.* Besides, organizations also need guidance on how to proceed to reach the target state [4], [7] by prioritizing and structuring the identified measures [6] to coordinate the initiatives with regard to limited resources and predecessor-successor dependencies. As the company-wide adoption of BDA requires a long-term evolution [3] and high investments [6], definition of milestones might help to reevaluate and terminate the transformation project, if necessary. We therefore define the following design principle: *(DP.2) The method should allow for prioritizing and structuring the implementation measures according to the BDA capability developed by them and to the time of their implementation. It should further enable defining the milestones for reevaluation.*

### *III.2.4.2 Method Procedure Model*

In keeping with [15], our method consists of activities (E.1), each of which includes techniques (E.2), tools (E.3), roles (E.4), and output (E.5) as summarized in Table III.2-2. Our method comprises three activities: defining the target state, identifying and prioritizing the gaps, and deriving a BDA roadmap. Although tools can be defined as IT tools only, we use a broader definition of [15], [16] and focus on tools that support the application of one or more techniques.

| Activity | Technique | Tool | Role | Output |
|---|---|---|---|---|
| Activity 1: Defining the target state | Define the target state based on selected dimensions | Roadmapping, BDA capability model, discussion | (Senior) Managers, project team | Target state, layers, sub-layers, fields of action |
| Activity 2: Identifying and prioritizing the gaps | Capture the status quo, identify and prioritize the gaps | Semi-structured interviews, fulfillment-importance matrix | Stakeholder, (senior) managers, project team | Fulfillment-importance matrix with prioritized gaps |
| Activity 3: Deriving a BDA roadmap | Derive and structure measures to close the gaps | Roadmapping | (Senior) Managers, project team | BDA roadmap with structured measures |

**Table III.2-2:** Overview of method's activities and elements

### Activity 1: Defining the target state

*Technique*: According to [12], activity 1's purpose is to address the question "Where do we want to go?" and to define the target state to be achieved by the adoption of BDA. First, the method user needs to define a target vision to have a common understanding of the target state. For companies that aim at using BDA as a competitive differentiator, becoming an IDO can be an appropriate target vision. In order to avoid a target vision being almost unattainable or only achievable with a great deal of effort, the method user can derive a second target vision as an intermediate step positioned between the status quo and an IDO. Furthermore, the intermediate step might allow a reevaluation of the targets and even a termination of the project, if necessary. Based on the defined target vision, the method user should define requirements that need to be fulfilled at the target state and group them according to appropriate dimensions to conceptualize the target state. Later on, these dimensions will be visualized as layers in the BDA roadmap. Since development of BDA capabilities can be an appropriate way to become an IDO, we recommend that selected BDA capabilities be used as roadmap layers. After conceptualizing the target state, the method user should operationalize it by breaking down the requirements into fields of action and group them into roadmap layers or sub-layers. The number of sub-layers should meet the appropriate degree of granularity. While too many sub-layers lead to a very detailed and overloaded roadmap, too little sub-layers would make it difficult to derive effective measures to close the gaps [12]. We recommend deriving a maximum of 5 – 8 sub-layers for any layer [12.

*Tool*: We recommend that all the activities of our method should be based on the roadmapping as a structuring approach [12] and techniques such as brainstorming and moderated group discussions [15] to generate and evaluate ideas. In order to derive layers and sub-layers of the roadmap, the method user can base on BDA capability models (e.g. [1], [8], [11]).

*Roles*: In order to carry out all activities of our method, we recommend that a project team, which can consist of internal and / or external experts in BDA and developing roadmaps, be assigned. The project team prepares and moderates discussions, interviews, and workshops. They also consolidate and analyze the input, and provide outputs. Since management support is a well-known success factor for projects with high transformation potential like the company-wide adoption of BDA [4], [6], activity 1 involves (senior) managers who are familiar with the organization's strategy.

*Output*: Activity 1's output is the target state(s) as well as fields of action grouped into layers and sub-layers.

**Activity 2: Identifying and prioritizing the gaps**

*Technique*: Consistent with [12], activity 2 aims at addressing the question "Where are we now?" as well as identifying and prioritizing the gaps between the status quo and the target state. In the first step, the method user needs to identify the experts who can give input on the derived fields of action (cf. *Roles* below). In the next step, they need to collect quantitative and qualitative data for further analysis to identify and prioritize the gaps by, for example, using the tools described below.

*Tool*: We recommend using semi-structured interviews [17]. The method user can include selected follow-up questions that match with the interviewees' areas of expertise to gain more insights. They can also include overarching questions to bring out the interviewees' expectations concerning their perceived challenges and opportunities regarding the company-wide adoption of BDA. In order to assess the status quo of fields of action in terms of their relevance and degree of fulfilment, we recommend using five-point Likert scales with 1 = irrelevant / not fulfilled at all and 5 = highly relevant / completely fulfilled. For identifying and prioritizing the gaps, the method user can adapt the fulfillment-importance matrix, which slightly resembles a mirrored version of Gartner's Magic Quadrant [18]. Therefore, they need to assign the fields of action according to their assessment of the matrix's four quadrants: "Invest!", "Manage Excellence!", "Reprioritize! or Disinvest!", and "Ignore!". The fields of action in the "Invest!" quadrant are the most important gaps and need to be closed by moving the associated requirements to the "Manage Excellence!" quadrant.

*Roles*: We recommend that the project team prepares, conducts, and analyzes the interviews. In order to gain sufficient information for a comprehensive report on the status quo, experts from different management layers and stakeholder groups should be interviewed (e.g. IT, finance, risk management, and sales departments). If necessary, the project team should consult the (senior) managers to identify the appropriate experts. Internal experts from projects with a similar focus (e.g. data quality projects) as well as external experts (e.g. consultants) that accompany these projects can also be interviewed. Each interview should be conducted by at least two project team members to avoid subjective interpretations of the answers.

*Output*: Activity's 2 output is a fulfillment-importance matrix with prioritized gaps.

**Activity 3: Deriving a BDA roadmap**

*Technique*: Following [12], activity 3 aims at addressing the key question "How can we get there?", as well as identifying the measures to close the gaps and structuring them in a roadmap. Method user should derive the measures and assign them according to the roadmap's sub-layers and layers. In terms of timeframe, the measures need to be structured according to their short-, medium-, and long-term perspective. Since the company-wide adoption of BDA requires a long-term evolution [3], a BDA roadmap might have a timeframe that spans over several years. Thus, the method user should consider intertemporal and scheduling interactions between the measures [6].

*Tool*: For identifying appropriate measures to close the gaps, method user can rely on knowledge about IDO, BDA, and BDA capabilities as well as brainstorming and discussions within the project team. For the latter, method user should be aware of limitations of relying on existing personal knowledge of the involved practitioners. A close collaboration between researchers and practitioners can help to reduce this bias if an intensive and reflective discussion process is ensured to combine the perspectives and insights from researchers and practitioners. For structuring the measures, we recommend deriving a roadmap as an established planning tool [12]. Thereby, the layers and sub-layers are based on the BDA capabilities derived in activity 1. The timeframe includes short-, medium-, and long-term perspectives.

*Roles*: The project team derives the measures to close the gaps from the literature, structures them in a roadmap, and evaluates the results with the (senior) managers.

*Output*: The output is a BDA roadmap with structured measures.

### III.2.5 Evaluation

#### *III.2.5.1 Case Study Setting*

We conducted our study in the strategic department of one of the leading universal banks in Germany. Since the banking industry is exposed to increasing innovation pressure through changing client behavior [19] and new market players like FinTechs [20], financial service providers need to innovate their current value delivery and interactions with clients [21] through providing data-driven services, for example. As a financial service provider, the case-study bank particularly had a large volume of client data such as details on repayment behavior and outstanding loans or credit lines. However, the bank failed to systematically get value from its data and it also failed to provide data-driven services to its clients. Thus, the bank aimed at adopting BDA across the whole company to develop it towards an IDO and to capture BDA potentials like strengthening innovative power and improvement of decision-making. However, the bank faced various challenges for this project. For example, a lack of end-to-end processes, a lot of manual work involved in the processes and thinking in silos led to frequent breaks in information flows. In addition, the bank had a partially outdated IT architecture and outsourced IT. Finally, the bank put a lot of effort into regulatory-driven projects and thus had rather limited human and financial resources for innovation projects. This led to a lack of awareness for innovation projects in general and for a company-wide adoption of BDA in particular.

The objective of the case study was therefore to develop a method for structuring the company-wide adoption of BDA to shift the company toward an IDO. Thereby, the head of the strategy department and the CIO, who recognized the market relevance of BDA, were looking for a method that would allow them to show the potentials of BDA to create awareness and to include the entire organization as well. With regard to the challenges highlighted above, the new method should consider various perspectives (e.g. people and processes) to enable including different stakeholder groups and levels of the enterprise architecture. Since the board of directors would have to approve the new initiative, the new method should also allow to assess what exactly they want to achieve with the company-wide adoption of BDA, what the status quo looks like and how they aim to achieve the target state. Due to the high complexity of the project, the new method should provide guidance in covering which adoption measures are necessary, how long the adoption will last, whether there are dependencies between the measures and which resources will be necessary for their implementation.

The project team consisted of five academic members from the authors' institutions (two research fellows and three professors) with expertise in developing digital roadmaps and in the financial services industry. In addition, the project team included four members of a consulting company (two consultants and two senior consultants) with BDA expertise and experience in regulatory-driven projects conducted at the case-study bank. The head of the strategy department and his assistant were also part of the team. The external project team's role was to prepare and conduct workshops, as well as interviews, and to develop the BDA roadmap. The project lasted three months in total. The external team members mostly worked in the back office and were on site for workshops, interviews, and other meetings. The external project team predominantly worked three to four days a week on the project and spent the rest of the time synchronizing with colleagues who were working in similar areas.

#### *III.2.5.2 Method Application*

**Activity 1: Defining the target state**

In order to create a common understanding of the target vision, we first discussed the meaning of an IDO with the head of the strategy department and the CIO. Thereby, we defined an IDO as follows: An IDO anchors data-based decision-making processes throughout the company and classifies big data as a core capability with the aim of making value-creating insights available at the right place and at the right time. According to the feedback of the bank end-users, we derived a second target vision as an intermediate step on the way from the status quo to an IDO to take into account the current challenges of the bank (e.g. a lack of resources and awareness). Since a company-wide adoption of BDA requires high investments, this step was also defined as a milestone for reevaluating the targets and the project to adjust the resource allocation or to determine the project, if necessary. In order to better express the focus of both target visions, we named them "Lab" and "Factory". Following the recommendations of prior research (e.g. [4], [5], [9]), the target vision "Lab" aimed at using BDA in selected business units – mostly in the form of lighthouse projects, – which should serve as enabler of strategic corporate goals. The target vision "Factory" focused on a group-wide use of BDA as a competitive advantage and unique selling proposition in an IDO context. In the next step, we conceptualized the target states by deriving the roadmap layers based on five BDA capabilities of strategy, people, process, data, and technology. Since a company-wide adoption of BDA influences different levels of the enterprise architecture, the BDA capabilities should be oriented at these levels. With this in mind, we first drew up a list of possible BDA capabilities based on literature research and selected the most important ones for the bank in a workshop with the head of the strategy department. For example, developing strategy and people capabilities might help to increase company-wide awareness for BDA, whereas process capabilities would allow accelerating innovation and decision-making processes. Since BDA requires an excellent handling of data and advanced technologies to collect, store and analyze it, the bank finally needed to develop data and technology capabilities. In close collaboration with the head of the strategy department, we assigned the defined target visions to the layer strategy. We then derived requirements to be fulfilled at the target states and grouped them into the remaining layers as summarized in Table III.2-3.

| Layers | "Lab" | "Factory" |
|---|---|---|
| Strategy | Use of BDA in selected business units in the form of lighthouse projects which serve as enabler of strategic corporate goals | Group-wide use of BDA as a competitive advantage and unique selling proposition in the sense of an IDO |
| People | Specialists in selected functions | Specialists in all functions |
| Process | Focus on lighthouse projects to create awareness | Integration into daily processes |
| Data | Data standardization within the lighthouse projects | Data lifecycle management |
| Technology | Focus on visualization software | Use of advanced BDA tools |

**Table III.2-3:** Target states at the case-study bank with selected requirements

Thereafter, we specified the requirements by breaking them down into the fields of action and grouping them into roadmap sub-layers. In sum, we derived twenty four fields of action (e.g. specialists, research environment, idea generation, and agility) and seven sub-layers (team structure, broad knowledge, innovation process, project management, data quality, data access and trust, and toolkit). Due to the challenges described above, several fields of action aimed at improving innovation processes (in particular increasing their speed) and promoting interdisciplinary collaboration to counter silo thinking.

**Activity 2: Identifying and prioritizing the gaps**

We conducted eleven semi-structured interviews with heads and members of different departments (e.g. finance and IT), as well as internal and external experts involved in regulatory-driven projects (e.g. AnaCredit and BCBS#239). The interviews followed the fields of action defined in activity 1. In close collaboration with the head of the strategy department, we excluded the strategy capability from the questionnaire, because it was defined through the target visions. Each interview was conducted by at least two external project team members and lasted roughly one hour. The interviewed experts answered the questions for each field of action and assessed the relevance, as well as degree of fulfilment, on a scale of 1 to 5 with 1 = irrelevant / not fulfilled at all and 5 = highly relevant / completely fulfilled. We also included follow-up and overarching questions to gather qualitative data for further analysis.

In the next step, we aggregated the quantitative results for each field of action and assigned them to quadrants of a fulfillment-importance matrix as shown in Figure III.2-1. According the five-point Likert scale, we defined the quadrants of the fulfillment-importance matrix by interpreting fulfillment values less than or equal to 3 and importance values less than 3 as low. We treated all fields of action located in the “Invest!” quadrant as gaps with a high priority and the fields of action assigned to the “Manage Excellence!” quadrant as gaps with medium to low priority. Based on our analysis, there were no fields of action assigned to the “Reprioritize! or Disinvest!” and “Ignore!” quadrants. This is reasonable, because evaluating the fields of action with practitioners and end-users in activity 1 already ensured that the most relevant fields of action were identified, also considering the organizational idiosyncrasies. We further evaluated the matrix by analyzing the qualitative insights from the follow-up, as well as overarching questions, and discussing our results with the head of the strategy department. Our first result was that the bank did well in a few central topics of the company-wide adoption of BDA, since many fields of action were located in the “Manage Excellence!” quadrant. For example, the bank made an effort to establish a data quality awareness within regulatory-driven projects. Most interestingly, the fields of action located in the “Invest!” quadrant were distributed almost equally across the four BDA capabilities. Therefore, deriving a BDA roadmap as a purely IT-driven effort would have neglected a substantial share of the relevant gaps. The gap analysis revealed that the first step was laying the foundations for an IDO by, for example, establishing a team of specialists, introducing an explicit research environment, and adopting basic technologies. On this basis, the bank could then begin with the more culture-oriented shift toward an IDO by focusing on generating innovative ideas, agility, and speed when it comes to the implementation of ideas.


**Figure III.2-1:** Fulfillment-importance matrix at the case-study bank

### Activity 3: Deriving a BDA roadmap

We derived measures to close the gaps based on the literature review, as well as discussions with the head of the strategy department and the CIO. In the next step, we structured the measures in the transformation roadmap in terms of sub-layers and timeframe-dimensions. We also delivered a comprehensive documentation with a detailed description of each measure. For anonymization reasons, Figure III.2-2 shows only a high-level transformation roadmap with selected measures structured into five layers (i.e. strategy, people, process, data, and technology) and three timeframe-dimensions (i.e. short-term phase 1, medium-term phase 2, and long-term phase 3). The target vision "Lab" should be reached at the end of phase 2, and the target vision "Factory" at the end of phase 3. Thereby, the planning reliability and granularity of measures are greatly reduced in phase 3 due to its long-term focus. We also included phase 0, which indicates the project start in the current year, as well as two evaluation loops at the end of phase 1 and phase 2 as a reevaluation or termination option.

In order to reach the target "Lab", within phase 1 and phase 2, we structured the measures aimed at creating BDA awareness and initiating a data-driven culture via lighthouse projects. These measures include, for example, recruiting internal and external specialists, as well as providing a research environment and technologies to carry out initial lighthouse projects. Further, measures like conducting lighthouse projects, providing the first prototypes through agile methods, and design thinking should foster idea generation, organizational agility, and speedy ideas implementation. The measures in phase 3 aimed at closing the gaps to reach the target vision “Factory”. Measures like organization-wide training programs in BDA or agile (innovation) project management approaches should ensure innovativeness and speed. Organization-wide data quality measures need to enable a high-quality data as basis for BDA. Further, measures like the implementation of a data lake architecture and a central sandbox should provide a flexible and scalable technological base that e.g. allows for adopting various BDA technologies. In close collaboration with the head of the strategy department, we also included strategy-related measures in our roadmap (e.g. change management, as well as strategic alignment between BDA measures and ongoing IT and regulatory-driven projects).

| | Start<br>Phase 0 | Lab<br>Phase 1 (short-term) | Lab<br>Phase 2 (medium-term) | Factory<br>Phase 3 (long-term) |
|---|---|---|---|---|
| **Strategy** | • Change management: Promoting agility & innovation, embedding BDA in corporate culture, developing a CoE for BDA<br>• Strategic alignment: Closely interlinking BDA and IT roadmaps as well as regulatory projects | | | |
| **People** | Set-up of the BDA transformation project<br>• Kickoff<br>• Detailed planning<br>• Concretization of the roadmap<br>• Preparation and start of initial measures | • Internal and external specialists<br>• Trust through lighthouse projects | • Individually training programs<br>• BDA goal for middle management | • Training programs for specialists<br>• Company-wide education programs |
| **Process** | | • Agile project methods<br>• Simplified administrative processes | • Innovation management for BDA<br>• Explicit BDA process | |
| **Data** | | • Mirrored database<br>• Program for data quality | • Data integration within the pilot areas<br>• DQM in the pilot areas | • Enterprise data framework<br>• Company-wide DQM |
| **Technology** | | • Software for the lighthouse projects<br>• Prototypes for lighthouse projects | • Software deployment process<br>• Lighthouse projects | • Cloud for high-performance analysis<br>• Systematic adoption of new technologies |

Completion & evaluation of first 2 lighthouse projects

Evaluation achievement target vision Lab & decision on expansion to Factory

**Figure III.2-2:** High-level BDA roadmap at the case-study bank

### *III.2.5.3 Method Evaluation*

Regarding the evaluation of design artefact, we can state that the new method that we co-developed and applied at a German bank provides an initial proof-of-value, since it fulfills the requirements of the bank outlined in Section 5.1. In particular, the new method enabled the bank to structure the company-wide adoption of BDA by deriving a roadmap that considers various perspectives (i.e. strategy, people, process, data, and technology) and prioritizes measures to close the identified gaps. Furthermore, the end-users evaluated the new method as understandable and practicable. Moreover, the board of directors accepted it and the bank has already started initiatives to implement first projects proposed in the roadmap. From a more abstractive point of view, our method fulfills the content and domain-specific requirements defined by the two design principles (DP1 and DP 2) in Section 4.1. According to DP1, our method allows defining one or more target states and their operationalization by considering selected BDA capabilities as shown in activity 1. In activities 2 and 3, it enables identifying gaps and deriving measures to close these gaps by involving different stakeholder groups (e.g. through interviews). Finally, the new method considers various levels of the enterprise architecture when defining the layers and sub-layers of the BDA roadmap. According to DP 2, our method allows prioritizing and structuring the implementation measures in a BDA roadmap as illustrated in activity 3. It also enables considering dependencies between individual measures and defining the milestones for the project reevaluation. Finally, our method meets general requirements for a new method because it contains the mandatory method components summarized in Table III.2-1. In terms of goal orientation, our method aims at structuring the company-wide adoption of BDA. As for principles orientation, our method is geared toward two design principles derived from the literature and fine-tuned with practitioners and end-users within an ongoing method evaluation by incorporating requirements outlined in Section 5.1. Repeatability and systematic approach are achieved by describing the method procedure model in detail and demonstrating its applicability at the case-study company.

Regarding the evaluation of design process, our method design follows the seven ADR principles. Within the first stage, we followed the ADR principle of practice-inspired research by illustrating that practice pays a lot of attention to BDA adoption. As for the ADR principle of theory-ingrained artefacts, our method bases on the existing knowledge related to BDA and roadmapping. During the second stage, we followed the ADR principles of reciprocal shaping and mutually influential roles, as well as authentic and concurrent evaluation by co-developing and evaluating our method in an iterative manner with the practitioners and the bank end-users. Through a continuous reflection on our method's design within the third stage, our method does not only reflect the preliminary design, but also the organizational shaping, as well as the practitioners' and end-users' feedback, thereby meeting the ADR principle of guided emergence. For example, activity 1 initially included defining one target state. After an evaluation with the bank end-users, we added the opportunity of defining more target states including a short explanation when it might be useful. In the fourth stage, we followed the ADR principle of generalized outcomes by providing general insights about activities for structuring a company-wide adoption of BDA.

### III.2.6 Conclusion

In this study, we investigated how organizations can structure the company-wide adoption of BDA. Using ADR, we developed a new method for structuring the company-wide adoption of BDA by deriving a BDA roadmap. Based on knowledge of roadmapping and BDA, our method includes three activities: 1) defining the target state, 2) identifying and prioritizing the gaps, and 3) deriving a BDA roadmap. Consistent with ADR, we developed and evaluated our method in a concerted research effort at a German bank.

Our work contributes to both research and practice. From an academic perspective, we enrich the body of knowledge related to BDA by linking the concept of BDA capabilities with the roadmapping approach when developing a new method for structuring the company-wide adoption of BDA. In particular, we show how companies can develop a BDA roadmap by considering BDA capabilities. Furthermore, we extend prior research on BDA capabilities by applying the concept of BDA capabilities to a concrete use case and illustrating how this concept can help to structure the company-wide adoption. Thus, our work can serve as a starting point for developing BDA maturity models and investigating their application in practice. Practitioners can use our method as a guideline for structuring the company-wide adoption of BDA. They can customize our method by extending our dimensions based on the BDA capabilities or by using other dimensions. Moreover, our research might help to develop company-individual methods for structuring other complex efforts like innovation and business transformation projects.

Our research has limitations that can serve as further starting points for future studies. First, we derived a customized BDA roadmap and noticed a lack of holistic BDA capability models that can be addressed by further research. Further, our method focuses on deriving a BDA roadmap as a planning tool and neglects the implementation phase. Research based on successfully carried out but also failed BDA adoption projects could be helpful for ex post analyses of success factors and development of key performance indicators to manage the adoption. Developed and evaluated at a German bank, our method is to a certain extent company-specific. Nevertheless, many aspects of our method can be generalized. As in our case, organizations should ensure a multidimensional view of the BDA adoption. Our experience also corroborates the importance of a close collaboration between strategy department, IT department, and business units, as well as the roadmap alignment to ongoing IT and regulatory-driven projects. Conducting further case studies might provide further valuable insights and outline possible differences along industries or the type of adoption projects. Despite its limitations, our research postulates a method for structuring the company-wide adoption of BDA and serves as a basis for further research aimed at closing the outlined research gap.

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## III.3 Research Paper 5: "Value of Data meets IT Security – Assessing IT Security Risks in data-driven Value Chains"

| | |
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| Published online in: | Electronic Markets, 2020, 1-17<br><br>This is the author's pre-print manuscript reprinted by permission from Springer Nature: Springer Nature, Electronic Markets, Value of data meets IT security – assessing IT security risks in data-driven value chains, Bitomsky, L., Bürger, O., Häckel, B., Töppel, J., Copyright © 2020, Springer Nature, advance online publication, 18 February 2020, https://doi.org/10.1007/s12525-019-00383-6. |

**Abstract:** *Digitalization forces manufacturing companies to shift towards a customer-oriented, highly data-driven value creation. This results in a changing IT security risk landscape as data becomes an attractive target for adversaries, leading to an increasing number of attacks. In order to protect data in an appropriate manner, it is essential to assess it in an integrated manner. Despite large research bodies regarding IT security and data-based value creation, existing literature fails to provide a guidance in the IT security risk analysis within data-based value chains. To contribute to the closure of this research gap, we propose a modeling approach, which allocates different data types to value activities and analyses them against selected IT security relevant risk properties. The conducted evaluation with industry experts reveals that not only a company's crown jewels can have severe impact but also less important data types with big exposure bear considerable IT security risks.*

### III.3.1 Introduction

Digitalization is continuing to significantly transform the way companies conduct business across all sectors of an economy, commonly enhanced through technological enablers such as big data analysis, cloud computing, mobile technologies and integrated sensor networks (Müller et al. 2016). Major trends such as servitization and Internet of Things (IoT) further amplify these changes, strongly promoting the shift from a product-centric to a customer-centric, highly data-driven value creation. However, interlinking data with a company's value creation also entails a shift in a company's risk landscape. First, increasing importance of data as a new value driver makes it an attractive target for adversaries, leading to an increasing number of attacks to steal, manipulate or deny the use of data. Further, data-driven value chains necessitate integrating data into products and services, sharing them with external partners and in-house which leads to new vulnerabilities and increases the attack surface. Moreover, the increasing dependency of products and services as well as the value chains themselves on data can lead to a considerable damage when data breaches occur. Increasing professionalism of hacker attacks and exponentially growing quantity of malicious software (BSI 2016) should also be taken into account. To protect their data in an appropriate manner, companies need to assess the IT security risks arising through the shift to a data-driven value creation to derive adequate security measures.

However, to date it is extremely challenging to assess the risks of data breaches due to the multitude of parameters that need to be taken into consideration. Moreover, a large research gap exists in the literature between data and value creation despite the fact that scholars and practitioners have shown data-based value creation a great amount of interest, particularly in the context of big data (Ekbia et al. 2015; Lim et al. 2017; Ostromet et al. 2015; ur Rehman et al. 2016; Yaqoob et al. 2016). While existing studies have identified the usage of data to be a key success factor with regard to customer satisfaction and have discussed the positive impact of integrating data into services and products, they to date fail to offer guidance in quantifying data in terms of value contribution and affiliated IT security risks. Although existing security standards require the value of data to be determined with respect to their importance for key business processes, they provide no further specification on how to perform this assessment. Therefore, a majority of companies still faces the challenge to identify their current and future data that contribute to the value creation (the so-called crown jewels), are critical from a security perspective, and thus need to be protected.

In order to bridge this research gap, we develop a model to assist the identification and allocation of value creation-relevant data types to individual value activities and the assignment of IT security risk properties. This allows for an assessment of data type integration into the value creation process with regard to the individual value contribution and affiliated IT security risks. Besides enabling comparison between data types with regard to their value and risk contribution, our model helps to identify a company's crown jewels from a data perspective and allows for simulations and assessment of potential future developments in business models in terms of value creation, e.g. a shift from a product-centric value creation towards stronger integration of information intensive services. Therefore, the objective of our approach is to lay groundwork towards data assessment in a value creation context, providing companies with guidance towards the identification of appropriate IT security investment strategies and bridging the existing research gap of connecting data and value creation from an IT security perspective.

The remainder of this paper is organized as follows: First, we provide a brief overview of literature related to data-driven value creation and data security. We then introduce the methodology we base on and develop the model for a value chain analysis and the calculation of the *Probability Weighted Risk Indicator* for risk analysis in data-driven value creation. Afterwards, we evaluate the model based on two real-world use cases and discuss the results and implications for companies' IT security investment strategies. We conclude by giving an outlook for further research.

## III.3.2 Literature Review

### *III.3.2.1 Data-Driven Value Creation*

A widely acknowledged concept for modeling value creation is the value chain of Porter (1985), initially introduced as a measurement tool for competitive advantage. It is based on the process view of a company and the idea of a (manufacturing) organization as part of a value system, including inputs, transformation processes and outputs as parameters. Stabell and Fjeldstad (1998) however argue, that the value chain is just one of three generic value configurations, as its application to service dominant industries is challenging. Therefore, based on Thompson's (1967) typology of long-linked, intensive and mediating technologies, they defined the three value configurations *value chain, value shop* and *value network*. While the value chain can be understood as the transformation of inputs into outputs by sequential activities resulting in interlinked chains, the value shop creates value by using existing company assets to resolve a particular customer problem. Therefore, resources and activities are selected and scheduled according to the problem at hand rather than following a pre-set sequence. The value network creates value by facilitating the linkage between two or more individual parties who wish to be interdependent. Activities involved in this process are often performed simultaneously, resulting in a layered, interconnected network of participants. In the past decades, there has been a shift from hierarchical, integrated, sequential supply chains towards strategic partnerships with external entities resulting in fragmented networks (Bitran et al. 2007). Especially digitally enabled networks experience rising popularity, as new digital technologies fundamentally reshape traditional business models into modular processes that are globally distributed and cross-functional (Sambamurthy et al. 2003; Straub and Watson 2001; Wheeler 2002).

Accordingly, a profound understanding of data-driven value creation is essential in the modern data-rich economy. However, despite a continually growing research body regarding data-driven value creation, particularly in the context of big data, there still exists a large research gap in the literature addressing the linkage of data and value creation in a holistic manner (Ekbia et al. 2015; Lim et al. 2017; Ostromet et al. 2015; ur Rehman et al. 2016; Yaqoob et al. 2016). Chen et al (2015) provide empirical evidence for the impact of big data analysis on business growth. Swanson (2001) finds a significant positive relationship between the use of data-based proactive maintenance strategies such as predictive maintenance and overall company performance measures. Yoo et al. (2014) show how hospitals enable medical practitioners as well as hospital administrators to enhance the quality of their service through the collection and analysis of operational data. These studies have identified the usage of data to be a key success factor in regard to customer satisfaction and discussed the positive impact of integrating data into services and products. Lim et al. (2018) further identified a research gap regarding the mechanisms behind these benefits, in other words how different types of activities and resources need to work together in order to create value. Based on the idea that value is created in the use of information and by applying the information within a process, they designed the “Data-Value Chain” within the context of information-intensive services (IIS) with the intent to supply a comprehensive framework to analyze and design the overall spectrum of value creation. While their study lays important groundwork towards understanding the transformation from data into value, they fail to provide answers on how to adequately measure the value of data and the final value contribution of that data to the overall value creation.

### *III.3.2.2 IT Security Risks*

A widely canvassed concept for information security threats is the distinction into unauthorized information release (confidentiality), unauthorized information modification (integrity) and unauthorized denial of use (availability), also known as the CIA triad (e.g. Anderson 1972; Saltzer and Schroeder 1975; BSI 2016) and considered as basic protection goals of information security. Due to the constant dynamic development of both information technology and information security threats, the CIA triad has been refined and extended throughout the years. However, our literature review shows that until now there is no agreed-upon set of goals exceeding the CIA triad. As data-driven products and services continue to change existing business models, information security gains new significance. The rising significance is confirmed by the exponentially growing number of security threats (BSI 2016) leading to increasing cost of a successful breach. For example, Grobauer et al. (2011) outline, that within cloud computing well-established vulnerabilities get enhanced as well as new vulnerabilities emerge. Based on estimation of Information Week and PricewaterhouseCoopers LLP, computer viruses and hacking took a "$1.6 trillion toll on the worldwide economy and $266 billion in the U.S alone" (Denning 2000). Thus, further research on the value of data with focus on its criticality and the impact of IT security breaches in needed.

Quantifying the exact impact of an IT security breach, however, is highly challenging due to the multitude of parameters to consider. The cost of an IT breach does not only comprise the short-term cost incurring during the period of the breach, such as lost business, decreased productivity due to unavailability of necessary resources and so forth (D'Amico 2000). In addition to these obvious costs, long-term costs such as costs related to customers who switched to competitors due to loss of trust, legal liabilities etc. incur, which are difficult to estimate (Cavusoglu et al. 2004a). To this day, most existing studies fail to adequately quantify the economic impact of IT security breaches on the companies, as they are based on self-reported company data, undermining the credibility of these estimations due to the tendency to revise the actual financial impact downwards or not to report it at all (Garg et al. 2003). A widespread approach, however, is an event-study methodology based on Fama et al. (1969) for analyzing abnormal returns during a pre-set time window around the event in question.

This methodology is highly popular in the accounting and finance literature (e.g. Koh and Venkatraman 1991; Friedman and Singh 1989). However, it has produced divergent results when applied to IT security breaches. Goel and Shawky (2008) analyzed the impact of 168 security breach incidents on the market value of publicly traded companies and present evidence, that such announcements had a negative impact of 1 percent on the market value during the days prior and after the security breach. Cavusoglu et al. (2004a) reported an average loss of 2.1 percent, translating into an average loss of $1.65 billion in market capitalization per incident. Garg et al. (2003) conducted a similar event-study using only 22 events, however gaining further insight by analyzing the type of security breaches, classifying them into four major incidents (web site defacement, DoS, theft of customer information, theft of credit card information). They present evidence, that theft of credit card information has the most severe impact with a fall by 9.3 percent on market value at the day of announcement and a significant 15 percent three-day negative reaction. Overall, their research results in a much higher impact than other studies.

A different approach was taken by Longstaff et al. (2002), who developed a Hierarchical Holographic Model (HHM) to assess security risks of IT based on the idea to integrate both exogenous and endogenous events into the risk analysis. Thus, they aimed to achieve a more holistic approach to the issue of modeling a complex system that is both interdependent and interconnected. Complementing these impact studies, research regarding the optimal investment strategies into IT security have emerged (e.g. Gordon and Loeb 2002). Cavusoglu et al. (2004b) present a conceptual framework regarding the optimal level of information security investments by taking the criticality of information and the associated loss with such criticality into account. They conclude, that organizations should concentrate on the protection of information with midrange vulnerabilities, as the benefits of protecting highly vulnerable information might not justify the inordinately expenses associated with it. However, the approach taken by the majority of existing literature is too generic to identify data's vulnerability and the loss associated with this vulnerability, as they take a holistic approach rather than mapping IT security risks to the associated data itself. Therefore, these approaches do neither offer any guidance in the identification of the company's crown jewels particularly worthy of protection nor their risk exposure.

With data-based services revolutionizing the way companies conduct business and create value, it is important to consider both the changes in value creation and in the risk landscape in order to protect emerging data-related crown jewels. However, recent research lacks approaches that allow for measuring the value contribution of data and analyzing the associated IT security risks in data-driven value chains. Nevertheless, in order to manage the risks of data breaches, it is essential to find quantification approaches, as within the risk management context, risk identification, risk analysis and risk evaluation are integral parts of risk assessment (Purdy 2010). Our objective therefore is to address this research gap by providing a modeling approach that links individual business data to value creation activities and allows assessing each data type in regard to its criticality and potential loss in case of a successful security breach. By distinguishing individual data types and their contribution to a company's value creation, data types become comparable. When carrying out simulations of potential changes in future value creation, these data types also become intertemporal comparable by early identification of a shift in the company's crown jewels. This lays groundwork for proper analysis of a company's current and future IT risk landscape and indicates possible directions for adjusting the IT security investment strategy.

## III.3.3 Model

### *III.3.3.1 Methodology*

In our approach, we mainly base on the methods of ontology development following Noy and McGuinness (2001) and normative analytical modeling as e.g. outlined by Meredtih et al. (1989). Thereby, we use ontology development for structuring the development process of our model and deriving its key parameters. The normative analytical modeling approach serves as basis for developing a key figure for quantifying IT security risks. Within the scope of this paper, we understand ontologies as "explicit specifications of conceptualizations" (Gruber, 1993, p. 199), meaning a formal and declarative representation of an abstract, simplified view of a real-world problem or situation. There have been many empirical studies concerning the proper development of ontologies. The method applied within the scope of this paper follows the approach presented by Noy and McGuinness (2001) who developed a seven-step guideline for the development of ontologies. Table III.3-1 shows how our approach follows this guideline. Normative analytical modeling captures the essentials of a decision problem by mathematical representations to produce a prescriptive result. Such analyses provide support in structuring decision problems, optimizing trade-offs among different criteria against a given target function and enable a well-founded choice between decision alternatives (Keeney and Raiffa 1993). Based on the classes and their properties derived through ontology development, we mainly follow Meredtih et al. (1989) and develop a model for IT security risk analysis in data-driven value chains. We then evaluate our model by means of two workshops with industry experts in order to validate the model parameters against applicability.

| | |
|---|---|
| 1) Determine the domain and scope of the ontology | The scope and intention of this model have already been declared in the Introduction. |
| 2) Consider reusing existing ontologies | Already existing ontologies could hitherto not be found. |
| 3) Enumerate all important terms in the ontology | As the focus of this paper lies on the identification of value-adding data types and their respective risk-relevant properties, we did not conduct this step to the required extend when developing a domain ontology but rather focused on the steps 4) to 7). Therefore, we only base on the results of our literature review. |
| 4) Define the classes and the class hierarchy | *Value Activities* with two subclasses Primary and Support Activities and further sub-subclasses. The subclasses of Primary Activities are Inbound Logistics, Operations, Outbound Logistics, Marketing & Sales, and Service. Analogously, the subclasses of Supporting Activities are Firm Infrastructure, Human Resource Management, Procurement, and Technical Development.<br>*Data* with subclasses (= *data types*) Logistic Data, R&D Data, Production Data, Distribution Data, Customer Data, IT Data, Financial Data, Personnel Data, and Strategic Planning Data. |
| 5) Define the properties (slots) of classes | Six properties have been identified overall. For the superclass *Value Activities*, this includes the intrinsic property *Value Contribution* $VC_i$ as well as the two types of inverse inter-class relations "*generates*" and "*uses*". The intrinsic and extrinsic properties *value contribution* $vc_{ji}$, *criticality* $k_{ji}$, *partners* $p_{ji}$, and *server interfaces* $s_{ji}$ where allocated to the superclass *Data*. |
| 6) Define the facets of the slots | All intrinsic and extrinsic properties defined are single cardinality slots, meaning they can only have one value at a time. |
| 7) Create instances | Instances are created in the Section "Model Evaluation". |

**Table III.3-1:** Reference overview of ontology development

### *III.3.3.2 Model Development*

In our model, we provide a two-phase approach. In the first phase, we derive an instrument for a value chain analysis that allows for identification of strategically important value activities within a company and the most important data types affiliated with these activities. In the second phase, we provide a procedure for IT security risk analysis based on the value chain derived in phase 1 to measure the value contribution of value activities and the associated data and their security-related criticality.

#### III.3.3.2.1.Phase 1: Value Chain Analysis

In order to properly assess data types with respect to their value contribution and criticality, a company must first identify its strategically important value activities and their affiliated data types.

**Assumption 1: *Value Activities***. Despite developments towards more sophisticated value creation networks in the recent years, we base on the framework of Porter (1985) to measure the value creation in order to keep complexity manageable within a first modeling approach. The framework states that within the course of value creation, a company performs activities to "design, produce, market, deliver and support its product" (Porter 1985, p.36). Thereby, Porter (1985) identifies nine generic categories of activities that can further be divided into primary activities and supporting activities. Primary activities are "involved in the physical creation of the product and its sale and transfer to the buyer as well as after sale assistance" (Porter 1985, p. 38). Five activities can be allotted to this category: *Inbound Logistics, Operations, Outbound Logistics, Marketing and Sales and Services*. While the primary activities each represent one process step of value creation, supporting activities are of a more complex nature. They provide support for both primary activities as well as each other and therefore can be associated with a specific value activity as well as the entire value chain. The supporting activities comprise of *Procurement, Technology Development, Human Resource Management, and Firm Infrastructure*. Thus, we define a *Value Activity* $VA_i$ with $i = 1, \ldots, n$ as an activity that is either directly involved in the value creation of the company or supports it.

We are aware that the value chain of Porter (1985) can probably not depict all idiosyncrasies of the value creation in highly digitalized and connected companies nor within digitalized business models. However, we can use it as a starting point for describing the value activities of classic manufacturing companies to reflect the potential shift from a product-centric to a service-centric world. It also helps to bridge the research gap of connecting data types to a company's value activities in order to evaluate the impact of IT security breaches on the overall value creation. It is important to stress however, that the value chain should not be considered as a strict sequential flow. Taking trends such as vertical and horizontal integration into account, the value activities should rather be seen as individual modules that can be used to map company individual value creation processes. Furthermore, while Porter (1985) understood *Services* to be of physical nature, e.g. maintenance or on-site installation, within the context of this paper we understand *Services* to additionally include data-driven services.

| Name | Definition | Sources |
|---|---|---|
| Logistic Data | Data associated with receiving, storing, and issuing production relevant inputs (e.g., supplier information, delivery status information, inventory information as well as route planning, vehicle fleet information and so forth). | Desrochers et al. 1992 |
| R&D Data | Data involved in and generated during an organization's efforts to either optimize a product and/or process or getting an innovation ready for the market. | Griliches 2007 |
| Production Data | Data associated with or generated during the transformation of inputs into the final product (e.g., process information, information about the product, the machine park, equipment maintenance, and quality testing). | Lee et al. 2014 |
| Distribution Data | Data involved in and generated during the collection, storage, and distribution of final goods to customers (e.g., warehousing and inventory information of finished goods, retailer information, distribution channel characteristics, delivery route planning, vehicle fleet information, and order processing information). | Gaynor et al. 2004 |
| Customer Data | Data related to or associated with the final customer and end-user of the product (e.g., personally identifiable information as well as information generated by sources such as customer service requests, mobile applications, social media networks, purchasing preferences and history as well as online browsing data). | Linoff and Berry 2011 |
| IT Data | Data related to the technical infrastructure of a company, comprising of hardware, software, and networks as well as IT development and any kind of coding generated or used within a company's operations. | Jeffery and Leliveld 2004 |
| Financial Data | Data related to financial transactions, financial property, and financial analysis (e.g., payment information as well as accounting details such as balance sheets, profit and loss statements, cash flow analysis, and stock information). | Merton 1976 |
| Personnel Data | Data associated with activities related to or involved in the recruitment, hiring, training, development, compensation, and dismissal of staff (e.g., personally identifiable information of employees, training material, professional development strategies, and compensation schemes). | Harter et al. 2002 |
| Strategic Planning Data | Data related to or generated during a company's process of determining the company's vision as well as identifying associated goals and objectives (e.g., a company's expansion and investment plans, vision statements, and business plan as well as actual state analysis, market and trend analysis). | Schwenk 1995 |

**Table III.3-2:** Overview of defined data types

**Assumption 2: *Data Types***. To link data with the value creation of a company, we need to identify the data types that contribute to value creation. Within the scope of this work, Data is defined as a set of qualitative and quantitative variables that exist in different forms and carry specific information that can be collected and analyzed. As addressed in the Literature Review, prior research lacks concepts, which define value-creation relevant data types. Therefore, we deduce nine key data types based on our literature review through grouping highly cited data types by common functions and departments found within an organization: *Logistic Data, R&D Data, Production Data, Distribution Data, Customer Data, IT Data, Financial Data, Personnel Data,* and *Strategic Planning Data*. To the best of our knowledge, consistent definitions of these data types have not been established in the existing literature. Therefore, within the scope of this paper, these nine data types are defined as summarized in Table III.3-2. Thus, we define a *Data Type* $D_j$ with $j = 1, \dots, m$ as a key data type that contributes to the value creation of a company. We are aware that these data types are generic containing multiple sub-categories, which may differ in their characteristics. Therefore, further company-individual specification is needed, also to avoid overlapping of data types within sub-categories. However, we abstain from a more detailed mapping for a first modeling approach to keep complexity manageable.

**Assumption 3: Allocation of *Data Types* to *Value Activities***. Each *Value Activity* $VA_i$ "uses and creates information, such as buyer data (order entry), performance parameters (testing), and product failure statistics" (Porter 1985, p.38). As *Data* has been defined as variables in various forms carrying information, the two inter-class relations "*generates*" $rg_{ij} \in \{0, 1\}$ and "*uses*" $ru_{ij} \in \{0, 1\}$ shall be assigned to each individual $VA_i$. Variable $rg_{ij}$ is a binary integer describing whether the *Data* $D_j$ is created by *Value Activity* $VA_i$, thereby taking the value 1 if *Value Activity* $VA_i$ creates *Data* $D_j$, and 0 otherwise. Variable $ru_{ij}$ is also a binary integer, describing whether the *Data* $D_j$ is used by *Value Activity* $VA_i$, thereby taking the value 1 if *Value Activity* $VA_i$ uses *Data* $D_j$, and 0 otherwise. Both are inversely related as they depend on a value of another slot (Noy and McGuinness 2001). The distinction between "*generate*" and "*use*" has to be considered in the subsequent risk analysis (phase 2) as according to the CIA principle, a data type which is not available after an IT security breach would primary affect activities that "*use*" this data. A confidentiality incident however would affect both using and generating activities, since hackers can access data in both cases. Regarding the intended use of this model, only combinations of $i = 1, \dots, n$ and $j = 1, \dots, m$ are considered, if their $ru_{ij} = 1$, ergo the *Data $D_j$* is *used* in *Value Activity $VA_i$*. Figure III.3-1 illustrates a template assisting the proposed value chain analysis.

| | Primary Activities | | | | | | | | | | Support Activities | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Value Creation Process** | Inbound Logistics | | Operations | | Outbound Logistics | | Marketing & Sales | | Customer Services | | Firm Infrastructure | | Procurement | | HR | | Technical Development | |
| **Data Type** | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use |
| Logistic Data | | | | | | | | | | | | | | | | | | |
| R&D Data | | | | | | | | | | | | | | | | | | |
| Production Data | | | | | | | | | | | | | | | | | | |
| Distribution Data | | | | | | | | | | | | | | | | | | |
| Customer Data | | | | | | | | | | | | | | | | | | |
| IT Data | | | | | | | | | | | | | | | | | | |
| Personnel Data | | | | | | | | | | | | | | | | | | |
| Financial Data | | | | | | | | | | | | | | | | | | |
| Strategic Data | | | | | | | | | | | | | | | | | | |

**Figure III.3-1:** Inter-class relations overview

### III.3.3.2.2.Phase 2: Risk Analysis

In this phase, we provide the key figures for quantifying IT security risks for the value activities and data types derived in phase 1. Therefore, we first define four properties of *Data* that focus on attributes relevant from an IT security risk perspective to consider individual data's criticality. In order to focus on the most salient properties, strong simplification is necessitated. Therefore, the following three questions should be answered:

1. What is the Data's value and its contribution to the company's success?
2. How critical is the Data? What are the consequences if the Data is leaked, compromised or (temporarily) unavailable?
3. How does the company's risk landscape look like and how many potential points of attack exist?

These questions are in line with the recommendations of the ISO/IEC 27002:2005, stating that companies should classify their information by sensitivity, criticality, and its value to the company's value contribution. Based on these questions, we then derive four properties, of which two cover the potential points of attack, to be incorporated into developing an indicator for measuring the risks for *Data.*

**Assumption 3.1:** ***Value Contribution***. The concept of Value Activities was developed by Porter (1985) in order to systematically examine and analyze the activities a company performs to gain competitive advantage. This implies the need to identify important activities and their contribution to the overall value creation. Based on that, we define *Value*

*Contribution* $VC_i \in \mathbb{R}_0^+$ as the value contributed by the *Value Activity* $VA_i$ to the total value created throughout a company's operation. It is important to stress that we neglect the value contributed by physical activities and solely focus on the value added by the use of data within activities. Thereby, value contribution $VC_i$ is a cardinal value expressed in monetary units with

$$\sum_{i=1}^{n} \boldsymbol{VC_i} = \boldsymbol{Total\ value\ (TV)}. \tag{1}$$

Analogously, each *Data* $D_j$ has a *value contribution* $vc_{ji}$ within the *Value Activity* $VA_i$. The value contribution of the *Value Activity* shall further be the sum of the value contributed by the individual data types used in this activity. Thereby, *value contribution* $vc_{ji} \in \mathbb{R}_0^+$ is a cardinal value expressed in monetary units with

$$\sum_{j=1}^{m} \boldsymbol{vc_{ji}} = \boldsymbol{VC_i}, \text{for all } i = 1, 2, \dots, n. \tag{2}$$

This only holds under the assumption that the overall value contribution solely reflects the data-driven added value and neglects the value added by physical components.

**Assumption 3.2: *Criticality*.** The second property is *criticality* $k_{ji} \in [0,1]$, measuring the criticality of *Data* $D_j$ in *Value Activity* $VA_i$. The most common approach when characterizing the criticality of critical infrastructures is "to assess the impact level in the presence of security-related threats" (Theoharidou et al. 2009, p. 36). As elaborated within the theoretical groundwork of our work, a widely canvassed conceptual model for information security threats is the CIA triad. Therefore, in order to determine the criticality value, each data type should be analyzed with regard to this concept. Thereby, a higher impact through a security threat leads to a higher criticality value. Hence, three parameters should be considered when allotting the criticality value: the impact of a *confidentiality breach* $c_{ji}$, an *integrity breach* $i_{ji}$, and an *availability breach* $a_{ji}$ of *Data* $D_j$ in *Value Activity* $VA_i$. All three indicators taking cardinal values between 0 (risk minimal) and 1 (risk maximal) according the CIA principle. Under the assumption of equal weighting among these three parameters, the final value for the *criticality* is per definition within this paper the maximum of the three parameters as seen in (3) resulting in

$$\boldsymbol{k_{ji}} = \boldsymbol{max}\,\{\boldsymbol{c_{ji}}, \boldsymbol{i_{ji}}, \boldsymbol{a_{ji}}\}. \tag{3}$$

**Assumption 3.3: *Potential Points of Attack.*** Regarding the potential points of attack, both company-internal and external factors are considered due to the constantly increasing use of cloud services and both horizontal and vertical integration in times of digitalization. Furthermore, the use of malware attacking both software and hardware has increased over the past years (BSI 2016, p. 18-21). To address this trend, within this paper the properties *partners* $p_{ji} \in \mathbb{N}_0\{\mathrm{p}_{ji}|\mathrm{p}_{ji} \in \mathbb{N}, p_{ji} \geq 0\}$ and internal *server interfaces* $s_{ji} \in \mathbb{N}_0\{\mathrm{s}_{ji}|\mathrm{s}_{ji} \in \mathbb{N}, s_{ji} \geq 0\}$ are defined as potential points of attack. As sharing information with collaboration partners leads to a simultaneous expansion of a company's potential attack surface, the property *partners* $p_{ji}$ describes the number of partners the *Data* $D_j$ is shared with within *Value Activity* $VA_i$, representing the company-external view of attack points. *Server interfaces* $s_{ji}$ follows the same logic from a company's internal view. By storing the same information on multiple server interfaces, a company distributes its IT security risk per data type, as a security breach on one server might not result in a complete loss or unauthorized modification of sensible data. On the other hand, it increases the number of attack points as the data is then accessible from not only one but multiple servers in case of a successful security breach.

We are aware that defining four data properties that are relevant for risk analysis cannot cover the wide range of possible properties. However, the selected properties can help to characterize the data regarding their risk contribution without losing relation to reality for the sake of simplicity within the modeling approach. Thus, the properties for every data type in every value activity can be expressed in vectors like

$$\boldsymbol{D_{ji}} = \begin{pmatrix} \boldsymbol{vc_{ji}} \\ \boldsymbol{k_{ji}} \\ \boldsymbol{p_{ji}} \\ \boldsymbol{s_{ji}} \end{pmatrix}. \tag{4}$$

**Assumption 4: *Probability Weighted Risk Indicator.*** Based on the identified value activities, data types, and their respective IT security relevant properties, in the next step, we provide a key figure for measuring IT security risks of data types.

For risk measurement, the expected loss (EL) is a common key figure (Sonnenreich et al. 2006). It is classically defined as probability of default (PD) times impact of default (I), in other words

$$\boldsymbol{EL = PD \times I.} \tag{5}$$

However, until now, determining the expected loss due to data security breaches is extremely challenging due to a multitude of parameters to be considered as discussed within the literature review. Therefore, we base on the idea of the EL and develop an impact indicator for estimating the potential damage based on a data type's value contribution and criticality. It further allows making different data types comparable to allocate adequate IT security measures. For that, we adjust the EL and introduce a *Probability Weighted Risk Indicator (PWRI)* in order to perform the risk analysis.

First, we calculate an *impact indicator* $X_{ji}$ measuring the impact of a successful security breach regarding *Data* $D_{ji}$ ($rg_{ij}$=1 or $ru_{ij}$=1)

$$\boldsymbol{X_{ji} = \left(\alpha \times \frac{k_{ji}}{\sum_{j=1}^{m} k_{ji}} + (1-\alpha) \times \frac{vc_{ji}}{\sum_{j=1}^{m} vc_{ji}}\right) \times VC_i\,,} \tag{6}$$

with $\alpha$ being a company-internally weighting factor for the importance of either value contribution or criticality. This formula implies that the risk indicator of a security breach regarding the *Data* $D_j$ used in *Value Activity* $VA_i$ is the product of the overall *Value Contribution* $VC_i$ of that *Value Activity* $VA_i$ and a weighted average of the Data's value contribution and criticality regarding that specific activity. Within the developed model, value contribution and criticality are modelled to be independent. We are aware that this might not always be accurate in reality as a higher value contribution might in some cases correlate with the data type's criticality. As this does not always necessarily hold (e.g., IT Data might have a low value contribution, but a high criticality due to its widespread use in supporting the value creation process), we abstain from modeling correlation.

The next step in calculating the *PWRI* is to define the *threat probability* (*TP*) of the *impact indicator* $X_{ji}$. As elaborated within the model development, the attack surface of a data type is covered by the internal and external points of attack, the quantity of which have been covered through $p_{ji}$ and $s_{ji}$. Further, within the scope of this paper, $\pi_p$ is defined as the probability that one of the external points of attack is successfully being compromised per year and $\pi_s$ is defined as the probability that one of the internal points of attack is successfully being compromised per year. Through the best practice security approach of IT segmentation (Binz et al. 2012), differentiated values for $\pi_s$ and $\pi_p$could be assigned depending on the respective security level of the used interface, but this has been excluded within this study for reasons of simplification. Finally, the probability that one or more external points of attack is being compromised can be expressed as the counter probability that no external point of attack has been successfully breached:

$$\boldsymbol{TP_{p_{ji}} = 1 - \left(1-\pi_p\right)^{p_{ji}},} \tag{7}$$

The probability that one or more internal points of attack are being compromised within a given time period $\boldsymbol{TP_{s_{ji}}}$ can be determined analogously. Therefore, the overall threat probability $TP_{ij}$ can be defined as

$$\boldsymbol{TP_{ij} = 1 - \left(1 - \pi_p\right)^{p_{ji}} + 1 - (1 - \pi_s)^{s_{ji}}} \,. \tag{8}$$

Now, the impact indicator $X_{ji}$ and the threat probability $TP_{ij}$ of that impact have been defined. Following the mathematical logic of the EL calculation, the $PWRI_{ji}$ can then be determined as follows:

$$\boldsymbol{PWRI_{ji} = X_{ji} \times \left(1 - \left(1 - \pi_p\right)^{p_{ji}}\right) + X_{ji} \times \left(1 - (1 - \pi_s)^{s_{ji}}\right)} \,. \tag{9}$$

The $PWRI_{ji}$ gives an indication of the expected potential loss in case of a successful security breach of data type *Dj* being used in the *Value Activity* $VA_i$. In order to compare the different data types and derive adequate security measures, the overall *PWRI* of *Data* $D_j$ must be considered. For simplification reasons within this model, the overall *PWRI* of *Data* $D_j$ can be calculated as follows:

$$\boldsymbol{PWRI_j} = \sum_{i=1}^{n} \boldsymbol{PWRI_{ji}}, \text{for } j = 1,2, \dots, m. \tag{10}$$

Companies can use these calculations resulting from the model in order to compare different data types within the company to determine the crown jewels, their exposure and allocate adequate risk measures accordingly.

Furthermore, this model and its implications can be used to provide a forecast on IT security risks that reflect changes in the IT security landscape, e.g. due to new digital business models. To do so, the time component $t \in \mathbb{N}_0$ must be introduced. A company must identify its current situation $t = 0$, fill the values of the property slots accordingly and calculate the *PWRI.*

$$\boldsymbol{PWRI_{j_{t=0}}} = \sum_{i=1}^{n} \boldsymbol{PWRI_{ji_{t=o}}}, \text{for } j = 1, 2, \dots, \mathrm{m}. \tag{11}$$

In a next step, a prospective business model according to the company's strategic vision must be determined, slots filled and the new *PWRI* for *t+1* calculated

$$\boldsymbol{PWRI_{j_{t+1}}} = \sum_{i=1}^{n} \boldsymbol{PWRI_{ji_{t+1}}}, \text{for } j = 1, 2, \dots, \mathrm{m}. \tag{12}$$

By comparing $PWRI_{j_{t=0}}$ and $PWRI_{j_{t+1}}$, adequate measures can be deduced, depending on the delta $\Delta PWRI_j$.

$$\Delta \boldsymbol{PWRI_j} = \boldsymbol{PWRI_{j_{t+1}}} - \boldsymbol{PWRI_{j_{t=0}}}, \text{for } j = 1, 2, \ldots, \text{m}. \tag{13}$$

A positive $\Delta PWRI_j$ indicates a rising expected damage due to a security breach regarding the *Data $D_j$*, hence a rising importance to effectively protect this data type. Analogous to that, a negative $\Delta PWRI_j$ indicates a decreasing damage in case of security breaches regarding the *Data $D_j$*. By identifying future needs early, investments in necessary security measures can be taken in advance to ensure tailored data protection. Of course, for reasons of conceptualization this is only a simplified approach to determine the impact of IT security breaches and thus should merely be considered as an indicator. However, it is an important first step towards quantifying data and its contribution to both value creation as well as risk.

### III.3.4 Model Evaluation

To challenge our model's intelligibility and applicability in practice, we evaluated it within expert interviews with two manufacturing companies. In order to consider different perspectives, we chose experts from two companies that differ in their organizational set up, industry and their digitalization maturity level. In each company, we conducted qualitative, semi-structured group interviews (Myers and Newman 2007) with experts who are involved in the company's business IT solutions and have a deep understanding of the company's value creation processes and the associated activities. The first company (C1) is an internationally operating corporation with approximately 15,000 employees around the world and annual sales of around 2 billion Euros. The company produces specialty glass and glass-ceramics for a variety of industries and considers itself an innovative, international leading technology group with a sole focus on B2B-interactions. We interviewed C1's director for business services and solutions (experience > 10 years), the head of process technology (experience > 20 years) and an IT Infrastructure & Security manager (experience > 5 years), hence executives from both the operational, value creation perspective and the IT perspective, ensuring credible results. While to date C1's production processes highly rely on integrated IT solutions in terms of monitoring and controlling, the product itself does not feature further applications making it a smart product nor is it likely in a future scenario. Instead, C1 increasingly searches for additional information intensive services complementing their products, generating additional value for the customer. The second company (C2) is a multinational corporation with approximately 27,000 employees worldwide and annual sales of about 4.4 billion Euros. The company develops and manufactures products, systems, software and services for the construction and energy industries and caters mainly to professional end-users (B2C). We interviewed C2's head of security and risk management IT (experience > 10 years), head of IT enterprise risk management (experience > 20 years) and an IT Infrastructure & Security manager (experience > 10 years).

After a short presentation of the developed model, the underlying assumptions and the intended use, the interviews were structured along the two phases of the model development, consisting of an interactive value chain analysis followed by a risk analysis. Furthermore, three categories (low (1), medium (2), and high (3)) for the underlying parameters of the risk analysis were defined for simplification and facilitation. This allows for a uniform scale facilitating communication and parameterization within the conducted workshops. The distinctive characteristics of these categories can be seen in Table III.3-3. For further, more deeply analysis, companies can use precise values instead of the scales provided in Table III.3-3.

| | Low (1) | Medium (2) | High (3) |
|---|---|---|---|
| Value contribution | Mere support process | Standard process (generates value, no core competency) | Core competency, main value driver |
| Criticality | | | |
| Confidentiality | Data partially publically accessible | For internal use only, widely accessible for all employees | Strictly confidential internal data |
| Integrity | Manipulated data is identified and output revised quickly | Manipulated data is identified or output revised quickly | Manipulated data cannot be identified quickly and output cannot be revised |
| Availability | Irregular data accessing | Near-time data usage | Real-time data usage |
| Point of attacks | | | |
| External partners | Only internal data storage | Access to few selected business partners | Shared access with a multitude of external partners |
| Internal server interfaces | Marginal data usage by services/applications. Access via company intranet only | Occasional data usage by services/applications. Access via intranet only | Regular, widespread data usage through diverse services/applications |

**Table III.3-3:** Distinctive characteristics of underlying parameterization categories

### *III.3.4.1 Results Phase 1: Value Chain Analysis*

The objective of the value chain analysis is to first identify the main value activities involved in a company's value creation and allocate the data types associated with these activities accordingly. As each activity uses a multitude of data, we put a focus on the most salient and important data types, limiting the allocation to a maximum of three data types per relation if possible. For C1, the experts identified the most heavily used data types to be Logistic Data, Production Data, Financial Data and Customer Data, each being among the most salient data types used within four value activities. This goes in line with C1’s strong focus on manufacturing. As production and input supply are closely linked and mutually dependent, production planning must be coordinated with the availability of necessary inputs for optimal operational activities. Furthermore, Customer Data is required during production for customer individual features and the customer individual issue of a quality certificate. Figure III.3-2 depicts the full data allocation of phase 1 conducted by the experts at C1, complemented by the value contribution of the value activities identified in phase 2.

| | Primary Activities | | | | | | | | | | Supporting Activities | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Value Creation Process** | Inbound Logistics | | Operations | | Outbound Logistics | | Marketing and Sales | | Customer Services | | Firm Infrastructure | | Procurement | | HR | | Technical Development | |
| **Data Type** | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use | generate | use |
| Logistic Data | x | x | | x | | | | | | | | x | x | x | | | | |
| R&D Data | | | | | | | | x | | | | x | | | | | x | x |
| Production Data | | x | x | x | | x | | | x | x | | | | | | | | |
| Distribution Data | | | x | | x | x | | | x | x | | | | | | | | |
| Customer Data | | | | x | | x | x | x | x | x | | | | | | | | |
| IT Data | | | | | | | | | | | x | x | | | | | x | x |
| Personnel Data | | | | | | | | | | | | | | | x | x | | |
| Financial Data | x | x | x | | x | | | x | | | x | | x | x | x | x | | |
| Strategic Data | | | | | | | | | | | x | x | | x | | x | | x |
| Value Contribution | | 2 | | 3 | | 2 | | 1 | | 1 | | 2 | | 1 | | 1 | | 3 |
| **Weighted** Value Contribution VCi | | 0,1250 | | 0,1875 | | 0,1250 | | 0,0625 | | 0,0625 | | 0,1250 | | 0,0625 | | 0,0625 | | 0,1875 |

**Figure III.3-2:** Value chain analysis results at C1

In comparison, due to C2’s orientation towards B2C-interactions, the experts identified Production Data, Distribution Data and Financial Data as the most heavily used data types in order to better cater to individual customer needs. During the value chain analysis, a need for more differentiated data types was expressed by both companies’ experts in order to achieve more sound results. However, both companies’ experts validated the real-world fidelity of the identified data types and value activities, agreeing that the model covers all relevant constellations that typically occur in their companies. They further confirmed the intelligibility of the model’s specifications for industry experts.

### *III.3.4.2 Results Phase 2: Risk analysis*

The risk analysis is conducted in a three-step process. First, the industry experts weighted the identified main value activities according to their share of the overall value creation by using the categories low (1), medium (2) and high (3) as displayed in Table III.3-3. Based on these weighting factors, the relative contribution of each value activity is calculated for better comparison. For a comprehensive overview of the weighted value contribution per value activity, refer to Figure III.3-2. For C1, the interviewees identified Operations and Technical Development as the value activities with the highest value contribution, making up almost 40% of the company's value creation, which goes in line with C1's business model focusing on manufacturing and innovation. Second, they conducted the parametrization of the identified IT security relevant risk properties, resulting in a risk property vector for each data type per value activity. In a third step, we use this parametrization to evaluate each data type by the means of the prior introduced *PWRI*. For simplification and facilitation purposes, the underlying parameters are again categorized into low (1), medium (2) and high (3) as displayed in Table III.3-3. Furthermore, $\alpha$, the weighting factor for the impact of a data type's value contribution and criticality, is pre-set to 0.5 and the probabilities of a successful IT security breach per year for internal and external attack points both to 5%. For simplification, we further base our evaluation only on data types with label "*use*" within all activities and exclude the "*generate*" column in Figure III.3-2. We determine these intrinsic values exemplary and are aware that these are company-individual and need to be adapted to individual use cases. For the values applied within the analysis, refer to Table III.3-4.

| | Low (1) | Medium (2) | High (3) |
|---|---|---|---|
| Value contribution | 0.1 | 0.5 | 1 |
| Criticality | 0.1 | 0.5 | 1 |
| External partners | 0 | 1 | 5 |
| Internal server interfaces | 1 | 2 | 10 |

**Table III.3-4:** Underlying model parameters

Applying these pre-set categories to the risk property vectors of each data type per value activity results in 27 vectors at C1 and 26 vectors at C2. To take potential future changes in their respective business model into account, we also capture the expectations of the industry experts on future developments, resulting in an additional 27 (26) vectors at C1 (C2). In order to quantify and compare data types, we insert the collected information from the experts at C1 and C2 into our model and calculate the impact of a successful security breach as a function of the data type's value contribution and criticality as well as the threat probability for each data type dependent on the data type's dispersion. Therefore, we insert the information of value contribution and criticality into formula (6) to calculate the impact indicator $X_{ji}$ and the collected information of internal and external partners into formula (8) in order to calculate the threat probability $TP_{ji}$. Plugging these results into formula (10), we derive the *PWRI* per both *Data* $D_j$ and the *Value Activities* $VA_i$. An exemplary risk property vector including results of Operations at C1 can be seen in Table III.3-5.

| | Logistic Data | | Production Data | | Customer Data | |
|---|---|---|---|---|---|---|
| | Current values | Exp. future values | Current values | Exp. future values | Current values | Exp. future values |
| Value contribution | 1 (0.1) | 1 (0.1) | 3 (1) | 3 (1) | 3 (1) | 3 (1) |
| Criticality | 2 (0.5) | 2 (0.5) | 3 (1) | 3 (1) | 2 (0.5) | 2 (0.5) |
| External partners | 1 (0) | 1 (0) | 1 (0) | 1 (0) | 1 (0) | 2 (1) |
| Internal server interfaces | 1 (1) | 1 (1) | 2 (2) | 3 (10) | 1 (1) | 2 (2) |
| Impact indicator Xji | 0.019 | 0.019 | 0.061 | 0.061 | 0.045 | 0.045 |
| TPij | 0.05 | 0.05 | 0.098 | 0.401 | 0.05 | 0.148 |
| PWRIji | 0.001 | 0.001 | 0.006 | 0.024 | 0.002 | 0.007 |

**Table III.3-5:** Operations risk property vector at C1 (Only "Use", model input values in brackets)

### *III.3.4.3 Result Analysis*

In this section, we show how the results yielded from our model can be analyzed and interpreted. In a first step, a company can identify its data-related crown jewels via the calculated impact indicator $X_{ji}$. As the impact consists of both the data type's weighted proportional value contribution and criticality, a high $X_{ji}$ implies a great significance regarding the company's value creation. Using this information, companies can derive measures to secure their data crown jewels. According to our model, for C1, Financial Data, Production Data and Customer Data have the highest impact indicator, together holding a share of 50% of the overall impact indicated. For all three data types, this can be explained by the high criticality affiliated with these data types. Thereby, confidentiality is the key criticality-driving factor for Financial Data and Customer Data as these underlie strict privacy policies and are heavily fined in case of unauthorized disclosure. The key criticality-driving factor of Production Data is integrity, as the C1's products underlie strict quality specifications that determine the product's stability and safety in use. In terms of crown jewels, the analysis yielded the same results for C2.

In addition, companies can rank data types in an integrated manner by comparing the calculated $PWRI_j$. According to our model, at C1, the data types with the highest $PWRI_j$ are

IT Data (PWRI=0.041), Financial Data (PWRI=0.027), Production Data (PWRI=0.026) and Logistic Data (PWRI=0.025), together making up 70% of the overall *PWRI*, with IT Data alone holding a surprisingly large share of 25% (see Figure III.3-3, grey bars). Financial Data, Production Data and Logistic Data yielded very close results with a delta smaller than 0.2% in regard to the overall share. The high $PWRI_j$ for IT Data is mainly driven by its application within Firm Infrastructure, as it does not only contribute high value and is highly critical, but more importantly is widely distributed both internally and externally, resulting in an exceptionally high threat probability. Same holds for Logistic Data, which is widely shared with external partners both within Inbound Logistics and Procurement, resulting in a relatively high overall threat probability for this data type. In contrast, Customer Data despite having a high impact value is generally kept in-house and shared with a minimal amount of parties, resulting in a significantly lower threat probability and therefore a lower overall *PWRI*. For C2, Customer Data (PWRI=0.036) yielded by far the highest *PWRI*, being nearly twice as high as the second most critical data type IT Data (PWRI=0.018). In addition to a high impact, Customer Data is widely distributed and shared with a high quantity of internal and external parties, resulting in an exceptionally high threat probability and therefore a high overall *PWRI*. The same logic applies to IT Data and Distribution Data (PWRI=0.012), both yielding a high threat probability due to wide distribution among internal and external partners. The wide distribution of these three data types can be explained by C2's business model with a focus on B2C-interactions offering a wide range of IT-enabled services complementing the physical products to their customers. For full results of the PWRI ranking refer to Table III.3-6.

| | Data Type | PWRI ranking at C1 | | Data Type | PWRI ranking at C2 |
|---|---|---|---|---|---|
| 1 | IT Data | 0.041 | 1 | Customer Data | 0.036 |
| 2 | Financial Data | 0.027 | 2 | IT Data | 0.018 |
| 3 | Production Data | 0.026 | 3 | Distribution Data | 0.012 |
| 4 | Logistic Data | 0.025 | 4 | Financial Data | 0.010 |
| 5 | Customer Data | 0.018 | 5 | Logistic Data | 0.009 |
| 6 | Distribution Data | 0.013 | 6 | Personnel Data | 0.007 |
| 7 | Personnel Data | 0.007 | 7 | Production Data | 0.005 |
| 8 | R&D Data | 0.007 | 8 | R&D Data | 0.003 |
| 9 | Strategic Data | 0.004 | 9 | Strategic Data | 0.001 |

**Table III.3-6:** PRWI ranking at C1 and C2

Another insight that can be gained from our model is the integrated view on a company's value activities by looking at the activity's cumulative *PWRI*. Intuitively, the activities with the highest contribution to the company's value creation seem the most at risk of IT security related attacks. However, according to our model, at C1 this is not the case. While Firm Infrastructure, Inbound Logistics and Services rank among the top three with regard to their respective PWRI, the experts assigned them a medium or even low level of value contribution. This can again be traced back to the data distribution in these activities, as they all feature data types widely shared with external and internal parties, offering a wide range of potential attack targets. This insight helps to raise companies' awareness for their potential weak links among their value creation process from an IT security perspective. At C2, the results did not deviate as strongly from the sole value contribution perspective.

Finally, our model can be used to analyze changes within the IT security risk landscape due to expected future business model shifts (featuring a stronger integration of information-intensive services, rising integration of smart products and smart solutions etc.). According to the experts at C1, changes are most dominantly expected in manufacturing processes and distribution activities by increasingly integrating smart solutions for better data analysis, individualized production and transparency towards the customer, resulting in a significant rise in the threat probability for Production Data and Customer Data. Another significant rise can be seen in R&D Data, which can be traced back to the increasing need to establish new collaborations in order to amplify IT innovations. This implies a rising need for integrated security measures taking complex collaboration-based ecosystems into account. Figure III.3-3 (red bars) illustrates the shift for C1. In contrast, having already reached a high digitalization maturity level, C2 does not expect a noticeable change in their business model during next years. Therefore, C2 aims for an overall increase of every data type's value contribution rather than for a shift within these data types regarding value contribution or criticality.

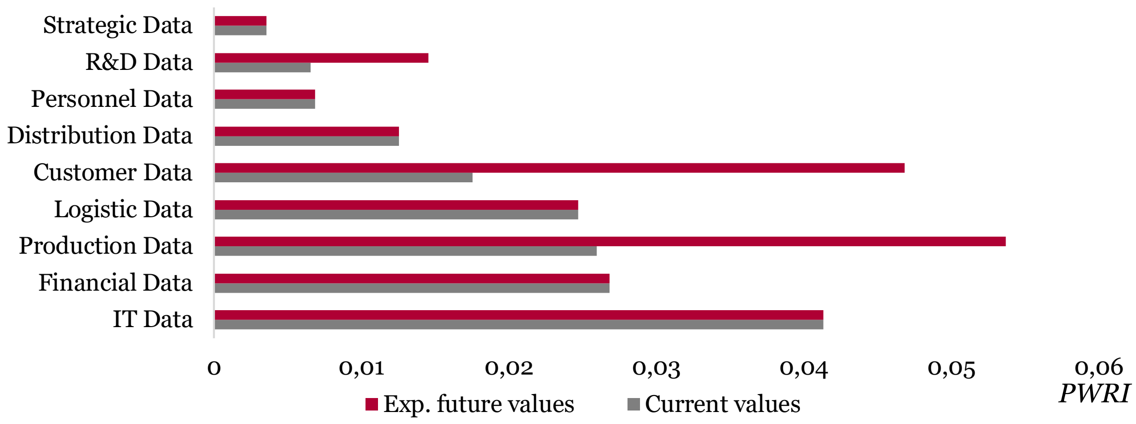


**Figure III.3-3:** Shift in threat landscape due to business model changes at $C_1$

As result analysis shows, our model provides support in assessing each data type with regard to its value contribution and criticality. Thereby, our aim is not to provide a model for calculating the exact loss in case of a security breach for each data type, but rather to derive a key figure for comparing and ranking data types in an integrated manner. By distinguishing individual data types and their contribution to a company's value creation, data types become both intra-temporal and intertemporal comparable, which allows for simulations and assessment of potential future developments. Furthermore, critical value activities and a company's crown jewels can be identified. Finally, companies can use such analysis as a first step to adjust their IT security investment strategies due to future changes in the threat landscape.

## III.3.5 Conclusion

Digitalization forces companies to challenge their business models and shift them to data-driven alternatives. Especially for manufacturing companies this leads to extensive changes in their value creation processes and in their IT security risk landscapes. To protect their newly emerged data-based crown jewels in an appropriate way, companies need to know what data contribute to their value creation today and in the future and how the associated risks can be measured. Despite a rich research body of IT security and data-driven value creation, approaches that link these disciplines and measure both the value and risk contribution of data in an integrated manner are still missing. Our approach aims at contributing to the closure of this research gap and supporting companies in analyzing IT security risks within their data-driven value chains. With this goal in mind, we provide a two-step approach. The first step, comprising a value chain analysis, allows identifying strategically important value activities and data types generated or used for these activities today and in the future. Within the second step, an integrated risk analysis, we derive the Probability Weighted Risk Indicator as a key figure to assess different data types with regard to their respective value contribution and the affiliated IT security risks. Among others, our model offers guidance in the identification of a company's crown jewels, their exposure and makes different data types comparable. We further evaluated our model with industry experts for real-world fidelity and applicability.

Our approach contributes to both research and practice. From an academic perspective, we lay important groundwork at the interface of IT security and data-driven value creation by providing an integrated modeling approach for IT security risk analysis combining these two research streams. In practice, our approach can be used for various analyses, e.g. to analyze the current state of the value creation by identifying the most important value activities and data types, hence the crown jewels of the company. Practitioners can also use the model to assess potential strategic business model developments and the associated shift in the value creation in an integrated manner. Thereby, applying our model can be the first step to identify potential risks associated with these shifts by analyzing different data types in the current and future value creation to identify the most critical data types and initiate discussions on mitigation measures. This also holds for project owners, who can use our approach to evaluate new project solutions regarding innovation or digitalization in order to illustrate the impact of their project solutions on the current value and risk contribution of the used data. Practitioners could further adjust our approach to consider a company's idiosyncrasies like stronger IT security guidelines by changing or expanding the model parameters.

Despite its contribution by providing first insights in IT security risk analysis of data-driven value chains, our approach has limitations that can be used as starting point for further investigations. For example, we base on the value creation approach of Porter (1985) as a first step to derive value activities. Researchers can use this as a starting point to further adjust the used approach or to evaluate alternatives to identify value activities within more complex interdependent value creation networks. We further derive key data types used in the value creation process from literature and evaluated them with industry experts. Further research could focus on other methods to identify key data types such as surveys or empirical investigations to ensure the generalizability of key data types. As the identified data types follow broad categories, potential overlapping of data within subcategories is not addressed, neither is the different degree of criticality of that data. An additional research path could therefore focus on splitting the identified key data types into more detailed sub-data types in order to allow for a more fine-grained analysis. This will benefit practitioners to identify mitigation measures in more detail such as which specific system to restrict access to and which employees may need a higher degree of vetting or more advanced training. Moreover, for the risk analysis, we consider four parameters to derive a risk indicator and thereby base on the concept of excepted loss calculations. Investigations on other appropriate risk parameters and measuring approaches would provide further valuable insights. Furthermore, until now it is a one-period model only, hence all decisions and outcomes occur simultaneously. Thus, dynamic aspects, such as spillover effects of a successful breach in one value activity to another are not considered yet and can be incorporated in the model. Furthermore, our model does not consider interdependencies and spread effects within the value chain and risk analysis. Further investigations on how these aspects can be incorporated in the approach could be helpful. Despite these limitations, our approach serves as an important first step towards IT risk analysis in data-driven value chains and as well as a starting point for further investigations in this area.

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# IV Results, Future Research, and Conclusion

This chapter contains the key findings of this doctoral thesis in Section IV.1 and an outlook on future research areas in Section IV.2. It also provides a short conclusion in Section IV.3.

## IV.1 Results

The main objective of this doctoral thesis was to contribute to (IT) innovation management by providing new approaches for the value-based IT innovation management. After motivating the importance of IT innovations and the need to manage them based on VBM principles, this thesis presented new approaches that support the value-based management of the creation and adoption of IT innovations. In the following, this section presents the key findings of the research papers of this doctoral thesis.

### IV.1.1 Results of Chapter II: Managing the Creation of IT Innovations

Chapter II focused on providing new approaches that support managing the creation of IT innovations. Overall, it presented two approaches for an ex ante financial evaluation of ITIPs to enhance their value contribution by balancing the associated benefits, costs, and risks, as well as allocating the limited resources in a way that is aligned with VBM principles. The first approach focused on the ITIP evaluation related to the application of OI to optimize the degree of openness (P1, Section II.1), whereas the second one dealt with the ITIP evaluation to optimize the team design (P2, Section II.2).

In Section II.1, research paper P1 focused on managing ITIPs carried out in collaboration with external partners (i.e., the OI paradigm). Thereby, P1 aimed at improving the value contribution of ITIPs by providing a value-based, ex ante evaluation approach that allows for optimizing their degree of openness to balance the trade-off between benefits, costs and risks of applying OI (Objective II.1). Using the normative analytical modeling approach, P1 drew from the knowledge of OI, research and development (R&D), and (IT) innovation management and developed a theoretical model for determining the optimal degree of openness in ITIPs. Based on a real-life case, P1 then demonstrated the model's applicability by calculating the theoretically optimal degree of openness in an ITIP for the concrete case. Further, P1 examined relevant causal relationships by analyzing how selected model parameters affect the optimum while using the simulation-based approach. The key findings of P1 were the following: First, finding the optimal degree of openness can help to increase the value contribution of an ITIP, and to outperform completely closed and completely OI projects due to an economically sensible balance between the associated benefits, costs, and risks. Second, applying OI in the idea generation phase tends to be more beneficial than applying OI in the development phase. Third, a company's ability to manage OI and the probability of success in OI application both strongly influence the optimal degree of openness. Thus, companies should work on improving both parameters to increase the value contribution of applying OI in ITIPs. P1's results contribute to scientific research by providing a new approach for a value-based, ex ante evaluation of applying OI at the project level that complements prior research, which has a strong focus on ex post analyses of applying OI at the organizational level. Practitioners can apply the new approach to measure the value contribution of applying OI in their ITIPs in order to find an optimal degree of openness instead of opening them on a gut feeling. Moreover, the new approach can help companies to cover and analyze the most critical influence factors as well as derive measures for ensuring a successful application of OI.

In Section II.2, research paper P2 also focused on managing ITIPs that aim at creating IT innovations. Thereby, P2 aimed at improving the value contribution of ITIPs by providing a value-based, ex ante evaluation approach that allows for optimizing their team design to balance the opposing effects of different design parameters on the performance (Objective II.2). Similar to P1, it followed the normative analytical modeling approach and developed a model for determining the optimal team design for ITIPs by referring to findings from research streams on team design, team performance, and IT innovation (projects). Using a simulation-based approach, P2 evaluated the model by calculating the theoretically optimal team design for an ITIP and analyzing the influence of selected team design factors on the theoretical optimum. In particular, it examined the performance of random team designs in contrast to the well-founded ones and pointed out that only 24% of ITIPs with a random team design had a positive profit. In contrast, for ITIPs with a well-founded team design, the profit was positive in 95% of all cases. To validate the model's assumptions and to illustrate its applicability in a real-life case, P2 also evaluated the new approach with two experts from practice. The key findings of P2 were the following: First, determining a (near) optimal team design for an ITIP leads to its considerably higher performance and outperforms projects with random team designs. Second, finding the right team size is very crucial as deviations from the optimum can result in a considerably lower ITIP's performance. P2 contributes to scientific research by providing a new approach for a value-based, ex ante evaluation of ITIPs related to the team design. It combines the research streams on team design, team performance, and IT innovation (projects) and provides first insights on how and to what extent various team designs might affect the value contribution of ITIPs. For practitioners, the new approach allows for a mindful team design by evaluating the impact of different team design parameters on the performance of ITIPs and by analyzing the consequences of deviations from the theoretical optimum.

### IV.1.2 Results of Chapter III: Managing the Adoption of IT Innovations

Chapter III focused on providing new approaches that support managing the adoption of IT innovations. Overall, it presented three approaches that aimed at assisting companies in evaluating investments in IT innovations with different maturity (P3, Section III.1), structuring the company-wide adoption of BDA (P4, Section III.2), and assessing IT security risks arising in manufacturing companies through the shift to a data-driven value creation (P5, Section III.3).

In Section III.1, research paper P3 investigated how companies can balance their investment strategy with regard to risk and return perspectives by engaging in fashionable and mature IT innovations. Since both IT innovation types are associated with different benefits and risks, P3 aimed at improving the investment strategy by developing a value-based, ex ante evaluation approach to optimally allocate a strategic IT innovation budget to IT innovations with different maturity (Objective III.1). Therefore, P3 referred to the central findings and ideas of IT innovation, IT fashion, and IT value theories as well as to prior work of Fridgen & Moser (2013), Häckel et al. 2013a, Häckel et al. 2013b, Häckel et al. 2016, Häckel et al. 2017, and Moser (2011) to develop a mathematical model for determining the optimal allocation of an IT innovation budget to mature and fashionable IT innovations. In contrast to prior studies, P3 focused on analyzing how company- and technology-specific factors influence the optimal allocation of a company's strategic IT innovation budget. Therefore, P3 evaluated the model by examining the impact of selected model parameters on the theoretical optimum while using a simulation-based approach. Based on prior work and the results received, P3 derived the following implications for research and practice: First, companies are well-advised to invest a certain share of their budget in fashionable IT innovations even if their success probability is still rather low. Second, investments in fashionable IT innovations in very early phases of their life cycle can be beneficial, even if a company's level of innovativeness and the technology's success probability are rather low. Third, companies should incorporate a technology's prospective impact and related success probability in the decision calculus. The new approach complements previous literature by analyzing essential causal relationships that may influence a company's IT innovation investment strategy. It also can help companies to plan and improve their IT innovation investment strategy with regard to fashionable and mature IT innovations based on an economic perspective.

In Section III.2, research paper P4 addressed the need of planning and structuring the adoption of IT innovations to ensure their long-term value contribution. Since IT innovations can affect various levels of the enterprise architecture, their adoption may be very complex as well as time- and cost-intensive. To approach this challenge, P4 aimed at assisting companies in planning and structuring a company-wide adoption of BDA by designing a roadmapping-based method (Objective III.2). Following action design research (ADR), P4 developed and evaluated a new method for structuring the company-wide adoption of BDA in a concerted research effort with a German bank. Based on the roadmapping approach, P4 derived the key activities, techniques, tools, outputs, and roles required for the new method. After deriving the design principles, it provided the procedure model for the new method including activities, techniques, tools, outputs, and roles derived. Using a case study at a German bank, P4 then illustrated the method's application in practice. P4 enriches the body of knowledge related to BDA by combining the concept of BDA capabilities with the roadmapping approach within a new method for structuring the company-wide adoption of BDA. Practitioners can use the new method as a guideline for structuring BDA projects or other projects with high complexity and transformation potential, for example the adoption of other IT innovations or digitalization projects.

In Section III.3, research paper P5 addressed the need for analyzing the changes that may arise through the adoption of IT innovations. Therefore, it focused on the changes in the IT security risk landscape of manufacturing companies caused through the adoption of BDA and aimed at enabling the assessment of IT security risks arising through the shift to a data-driven value creation by providing a modeling approach to analyze data types in terms of value contribution and affiliated IT security risks (Objective III.3). Based on ontology development and normative analytical modeling, P5 provided a two-phase approach. Whereas the first phase, value chain analysis, allows for identifying important value activities and data types generated or used for these activities, the second phase, risk analysis, enables assessing the identified data types with regard to their value contribution and the affiliated IT security risks. For the value chain analysis, P5 derived the key value activities and data types, as well as a technique to allocate the data types to value activities. For the risk analysis, it derived properties to measure the value contribution, criticality, and potential points of attack for each data type, as well as key figures to measure the IT security risks. P5 evaluated the new approach with industry experts for real-world fidelity and applicability, and provided a guideline how companies can analyze and interpret the received results. P5 contributes to scientific research by providing a modeling approach for IT security risk analysis that combines the research streams on IT security and data-driven value creation. In practice, the new approach can help companies to identify the data-related crown jewels, to compare data types in an integrated manner, and to examine changes within the IT security risk landscape due to expected future business model changes.

## IV.2 Future Research

To provide a concluding outlook on the research topics in this doctoral thesis, this section highlights potential aspects for future research for each chapter.

### IV.2.1 Future Research in Chapter II: Managing the Creation of IT Innovations

Although the new approach developed in P1 provides first evaluation of applying OI in ITIPs, it has some limitations that can serve as a starting point for further investigations. Thus, several assumptions made in P1 may limit the applicability of the new approach in practice to a certain extent and require a further investigation effort. For example, the model assumes five types of cash flows that may result within three phases of the innovation process and a planning horizon of three periods. Since companies may face various cash flows, which are often difficult to estimate and allocate in practice, future studies should fine-tune the model by including further cash flows and detailing the number of project phases. Further adjustments may aim at incorporating the innovation’s life cycle characteristics in place of modeling the cash inflows as a perpetuity, including non-deterministic costs, or considering different risk attitudes instead of assuming risk-neutrality. An empirical evaluation of the causal relationships identified by the model may be a promising subject to further research to assist companies in operationalizing the model. In particular, P1 covers the ability to manage OI as a crucial success factor in applying OI. Thus, further investigations on the key drivers of the ability to manage OI or measures to increase it may help companies to ensure a successful application of OI. Since P1 does not differentiate between different ITIP types, incorporating the idiosyncrasies of developing new products, services, processes or business models could be within the scope of further research. Finally, aspects like the type of OI activities or the characteristics of external stakeholders may be a topic of interest for further research as P1's analysis does not cover them in detail.

Regarding the evaluation of ITIPs related to their team design, P2 outlines several opportunities for future research mainly arising from its limitations. Since companies need to estimate the model's parameters, an empirical evaluation of the model in a given organizational context might help to strengthen the findings of P2 (Meredith et al. 1989; Wacker 1998) and provide further support for companies to operationalize the model. Furthermore, simplifying assumptions made in P2 can be a starting point for further investigations. Since P2 assumes two types of benefit factors, future research should challenge their actual financial interpretation and incorporate further relevant benefit factors (e.g., time-to-market and cost-to-market). Future studies may also extend the actual focus of P2 on a globally distributed innovation by investigating the differences between a locally and a globally distributed innovation (e.g., a new product), and their effects on the optimal team design. Since P2 considers selected team design parameters, future research may investigate which further important parameters can be incorporated in the model. For example, an expert interview revealed that factors like the ITIP goal, as well as team management and leadership skills are important in practice, and thus, should be considered in further research. Incorporating further internal and external factors as risk attitude, company size, and business environment can be also an interesting research area. Finally, further research on differences between innovation laggards, opportunistic adopters, and systematic innovators might provide a more detailed view onto the company's innovator profile and its impact on the team design.

In sum, the potential research opportunities outlined above may serve as starting points for further investigations and contributions toward managing the creation of IT innovations in a way that supports the principles of VBM.

### IV.2.2 Future Research in Chapter III: Managing the Adoption of IT Innovations

The approach for determining the optimal engagement in IT innovations with different maturity developed in P3 comes along with several limitations that represent areas for future research. To support companies in operationalizing the model by estimating values for its input parameters, future research may test the new approach against previous studies to analyze similarities and differences of the results, as well as empirically evaluate the model and its parameters using real-world data. Further research may also investigate the incorporation of further aspects in the model like switching costs or spillover effects. To address the risk of investing in a losing technology or of getting outpaced by competitors in more detail, future models may also incorporate a bankruptcy scenario and assume a risk averse decision-maker. Since the model in P3 is limited to quantifiable components of IT innovation’s value, incorporation of non-quantifiable components, such as soft benefits like a company’s reputation as an innovator, may be an interesting research direction. Further research may also consider different fashionable IT innovations by modeling them with varying parameters (e.g., technological impact factor or success probability). To evaluate the appropriateness of the new model for a concrete company, future studies should examine different internal and external factors that can influence a company’s IT innovation strategy (e.g., role of IT, company size, considered sector, or business environment).

The new method for structuring the company-wide adoption of BDA developed in P4 reveals various opportunities for future research. In particular, P4 covers a fragmented knowledge on how companies can use the concept of BDA capabilities to develop toward IDOs. Thus, future research may aim at developing holistic BDA capability and maturity models to close this research gap and can, for example, base on the results of P4 for developing such models and investigating their application in practice. Since the new method focuses on deriving the BDA roadmap as a planning tool, future studies may aim at investigating the implementation phase to support companies in managing the implementation of the roadmap measures. Thereby, studies on successfully carried out, but also on failed BDA projects could serve as a basis for conducting ex post analyses of success factors and developing key performance indicators to measure the success of BDA projects. Since the new method was developed and evaluated at a German bank, further studies (e.g., case studies) may aim at providing further insights, such as possible differences along industries or the type of transformation projects.

Although the new approach derived in P5 provides first insights in IT security risk analysis of data-driven value chains, it has several limitations that may provide opportunities for further research. Since the value creation approach of Porter (1985) used in P5 to derive value activities is more appropriate for a traditional value creation of manufacturing companies, future studies may aim at providing new approaches to structure value activities within more complex interdependent value networks. To derive key data types used in the value creation process, P5 refers to the literature and evaluates the selected set with industry experts. Thus, further investigations on methods to identify key data types such as surveys or empirical studies may ensure the generalizability and completeness of derived key data types. As P5 uses rather broad categories for the identified data types, it does not consider potential overlapping of data within subcategories or the different degree of criticality of that data. Thus, future studies that focus on splitting the identified key data types into more detailed sub-data types would allow for a more fine-grained analysis. Although the four risk parameters and the risk indicator derived in P5 may be one possible way to assess IT security risks, further investigations on other appropriate risk parameters and measuring approaches would provide further valuable insights. Since the new approach is a one-period model only, future studies may investigate the incorporation of dynamic aspects in the model. Finally, within the value chain and risk analysis, P5 does not consider interdependencies and spread effects. Thus, investigations on how these aspects can be incorporated in the approach could be a promising subject to future research.

In sum, the potential research areas outlined above may serve as a basis for further investigations and contributions toward a value-based management of the adoption of IT innovations.

## IV.3 Conclusion

Summarizing the research papers presented in Chapter II and III, this doctoral thesis contributes to the existing literature in (IT) innovation management by providing new approaches for managing the creation and adoption of IT innovations in a way that supports the principles of VBM. Although this doctoral thesis certainly can only answer some selected questions, it contributes to previous work by providing new insights in selected areas and thus, serves as a first step towards better managing IT innovations.

## IV.4 References

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