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Discussion Paper

Organizational Learning and the Error of Fixed Strategies in IT Innovation Investment Evaluation

by

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Completed Research Paper

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Abstract

Though many IT innovations do not meet the high expectations, the investment evaluation of fashionable IT innovations, that in contrast to mature IT innovations are currently hyped but lack broad institutionalization, often follow a gut feeling. To enhance a company's ability to innovate with IT, literature emphasizes organizational learning through continuous innovating. We extend existing IT innovation literature by developing a dynamic optimization model that determines the optimal allocation of an IT innovation budget to mature and fashionable IT innovations by considering organizational learning. As this theoretical optimum often cannot be implemented in practice, companies apply fixed strategies which seem to be suitable but do not consider the effect of organizational learning and the fashionable IT innovation's probability of success. We examine the evaluation error from under- or overinvestments in fashionable IT innovations and how this error is influenced by organizational learning and a fashionable IT innovation's probability of success.

Keywords: IS innovation, IT investment evaluation, IT fashions, IT strategy

¹ At the time writing this paper, Vasko Isakovic was a research assistant at the FIM Research Center

Introduction

Driven by market pressure and bandwagon behavior, many companies mindlessly rush into IT innovation investments without careful consideration even though many technologies often turn out to be failing technologies (Lu and Ramamurthy 2010; Swanson and Ramiller 2004). The high uncertainty about an IT innovation's development makes it difficult for companies to know whether it 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 it was the case for the WAP technology or virtual worlds. Due to their peculiarities like uncertain success probability, literature like Wang (2010), Baskerville and Myers (2009), or Fichman (2004a) defines those IT innovations which are undergoing a hyped phase as *fashionable* IT innovations. *Mature* IT innovations, by contrast, have already been widely accepted and have a higher probability of institutionalization. Hence, IT fashion research examines technologies which need to cross the chasm from being a fashionable IT innovation to being a more mature IT innovation (Wang 2010). Due to their novelty, immaturity and thus uncertain success probability, such new emerging technologies "[...] impose significant knowledge barriers that early adopters have to overcome [...]" (Ravichandran and Liu 2011).

To overcome such barriers and to enable a mindful evaluation and selection of IT innovations which are appropriate for an organization, literature emphasizes that companies have to "[...] undertake learning to bridge the gap between what they already know and what the new technology requires them to know" (Fichman and Kemerer 1997). Organizational learning thus improves a company's innovator profile, i.e., its skills regarding the comprehension, adoption, implementation and assimilation of new technologies (Ashworth et al. 2004; Fichman and Kemerer 1997; Salaway 1987; Wang and Ramiller 2009). To improve a company's ability to thoroughly select, evaluate and thus to engage mindfully in such risky fashionable IT innovations, sufficient and continuous organizational learning requires considering fashionable IT innovations not merely as a flash in the pan but as a persistent share of the IT innovation strategy (Stratopoulos and Lim 2010; Wang 2010). At the same time, it is important for a company to incorporate the market's innovation activities into the IT innovation process to make it difficult for the market's competitors to "[...] replicate a company's ability to innovate with IT over the long term" (Stratopoulos and Lim 2010). However, even though previous empirical and qualitative research demonstrated the relationship between factors like organizational learning, IT innovation investments and the ability to innovate with new emerging IT, researchers like Williams et al. (2009) demand for more variety regarding the methodology in IT adoption and diffusion research. In particular, the question of how a fashionable IT innovation's probability of success as well as organizational learning affect the engagement in such risky IT innovations (i.e., the allocation of an IT innovation budget to fashionable IT innovations) still remains unanswered. To provide first answers in form of theoretically founded propositions on what determines an organization's engagement in mature and fashionable IT innovations, we develop a dynamic optimization model which theoretically determines the optimal investment level regarding mature and fashionable IT innovations. By taking organizational learning and the IT innovation's probability of success into account, the model is able to carve out how those factors affect the level of engagement in mature and fashionable IT innovations. As our analysis' focus throughout the paper is engagement in fashionable IT innovations, our first research question is the following:

RQ1. *How do organizational learning and a fashionable IT innovation's probability of success affect the engagement in fashionable IT innovations?*

According to our theoretical model there exists an optimal allocation of an IT innovation budget to fashionable and mature IT innovations which for a company might serve as a basis for an appropriate evaluation, selection and thus a mindful investment. However, management's uncertainty, missing data or political reasons in practice often lead to rather fixed rules within IT innovation investment strategies (Nagji and Tuff 2012; Swanson and Ramiller 2004). Nevertheless, a mindful IT innovation engagement usually requires a thorough analysis of whether a technology is appropriate for the company which cannot be realized with a fixed allocation of IT innovation budget to fashionable IT innovations. Despite the fact that previous studies have found different fixed ratios to be suitable for different industries (Nagji and Tuff 2012; Ross and Beath 2002), such fixed strategies do not consider the effect of organizational learning as they are constant over time. Thus, they might deviate from the theoretical optimum and subsequently lead to a potential evaluation error due to over- or underinvestments in fashionable IT innovations. As the optimal allocation is supposed to change over time when considering the effect of organizational learning (which also changes the company's characteristics and thus a technology's

appropriateness), the evaluation error is likely to differ when applying a fixed strategy in a setting with or without the consideration of organizational learning. However, even in case a company incorporates organizational learning in its IT innovation strategy, the optimal allocation in particular still depends on a fashionable IT innovation's probability of success as well as a company's individual innovator profile. Thus, the error of over- or underinvestments due to fixed strategies is supposed to change with the fashionable IT innovation's probability of success as well as with a company's ability to innovate with IT. This raises our second research question:

RQ2. *How does a company's individual innovator profile and a fashionable IT innovation's probability of success affect the potential evaluation error of over- or underinvestments in fashionable IT innovations which results from common fixed strategies widely applied in practice?*

To approach these research questions we apply a design-science driven research, a well-recognized methodology that aims at creating and applying specific artifacts to gain knowledge of a problem domain which later might contribute to solve organizational problems (Gregor and Hevner 2013; Hevner et al. 2004; Peffers et al. 2008; Wacker 1998). Furthermore, this approach is closely related to the basic idea of the research cycle of Meredith et al. (1989), who emphasize that for research areas which have not been thoroughly examined yet, qualitative and mathematical approaches, which predict first results and propositions, provide the basis for generating hypotheses for future tests within empirical research. Hence, our research's focus is to illustrate and analyze important cause-and-effect relationships regarding two major factors which influence IT innovation investments rather than applying a normative approach that provides specific guidelines or recommendations for decision support. To reveal the effects of organizational learning and the fashionable IT innovation's probability of success on IT innovation investments as the two factors which are in focus of our analysis, we transfer central findings of IT innovation and IT fashion theory as well as aspects of organizational learning theory to a dynamic n-periods optimization model. This aims at understanding how these factors affect a company's engagement in mature and fashionable IT innovations. Knowing the theoretically optimal investment strategy allows us to analyze the potential evaluation error of over- or underinvestments in fashionable IT innovations that results from fixed investment strategies based on gut feeling decisions. Particularly, we aim at analyzing how a fashionable IT innovation's probability of success and a company's individual innovator profile affect this potential error in a model *with* as well as in a model *without* considering organizational learning. This analysis allows us to derive first propositions which build the basis for later research which aims at empirically testing the described effects. The paper is organized as follows: First, we describe the idiosyncrasies of an engagement in fashionable IT innovations in more detail and give an overview of the relevant IT innovation, IT fashion and organizational learning literature. After that, we develop and analyze our model to answer the stated research questions and derive first results and propositions. This serves as the basis for a discussion of the contributions to research and practice, possible limitations and the potential starting points for future research.

Problem Context and Related Work

To lay the theoretical foundation for our formal-deductive mathematical model, we first provide an overview of an IT innovation's lifecycle, then critically review previous IT innovation and IT fashion research and conclude by reviewing selected aspects of the organizational learning theory.

IT Innovation Lifecycle

Within their lifecycle of adoption (Rogers 2003), IT innovations are often accompanied by waves of both, discourse (=rumor) on the innovation as well as its actual diffusion and adoption (=technical implementation) (Abrahamson and Fairchild 1999). Both waves follow a lifecycle 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 and Raskino 2008). This concept illustrates the start of an IT innovation's lifecycle by means of a *technology trigger* and excessive publicity leading to over-enthusiasm and investments on the basis of bandwagon behavior. The hype usually reaches a peak of *inflated expectations* before it fades away in a *trough of disillusionment*. These three milestones mark the phase when an IT innovation has fashionable aspects and an unclear destiny. After this phase, opportunistic adopters often abandon ship, IT projects are scaled back and fashionable IT innovations might get stranded. Only few technologies are worth continuing and 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 and Raskino 2008). 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 institutionalized. In the subsequent sections, we show that common IT innovation literature tends to neglect these idiosyncrasies and discuss why IT fashion research is a valuable contribution to (IT) innovation literature, especially regarding the lack of quantitative models which can support the mindful selection and evaluation of IT innovations.

IT Innovation and IT Fashion Literature

Traditional IT innovation literature mainly focuses on a set of variables like company size, structure, knowledge, or compatibility which form the company's individual innovator profile that affects the extent and ability of IT innovation adoption (Grover et al. 1997). Companies fitting this profile are expected to innovate easier, more effective and consequently more economic (Fichman 2004a). However, several authors claim to consider other IT innovation related issues (e.g., probability of institutionalization, learning by doing, impact of the technology, intensity of the market's innovativeness) in the selection and evaluation of IT innovations (Fichman 2004). Swanson and Ramiller (2004) or Fiol and O'Connor (2003) argue that companies should innovate mindfully by considering different types of IT innovations in their IT investment strategy and by deciding whether an IT innovation is appropriate for the company. This also requires a well-founded analysis of different IT innovation investment alternatives which considers the expected destiny, i.e., that some IT innovations reach institutionalization whereas some are completely abandoned.

In contrast, IT fashion theory extends the traditional focus on company size, structure, knowledge, and instead argues that the massive adoption of *certain* (IT) innovations not only is to explain through their simplicity or possible productivity increase but also through its propagation as the basis of dramatic potential improvements. Companies thereby tend to adopt (IT) innovations that are in fashion in the course of an action that is often negatively depicted as "bandwagon effect" (Abrahamson 1991; Wang 2010). Literature justifies an own IT fashion research stream by the fact that in contrast to management fashions, IT fashions often come along with high switching costs through the restructuring of IT infrastructure, tangible artifacts like software and hardware and their uniqueness due to various company individual implementation details (Fichman 2004a; Wang 2010). Lee and Collar (2003) found that IT fashions occur more frequently than management fashions what requires separate attention. Literature in IT fashion research up to now is characterized by mostly qualitative or empirical papers which deal with the development, evolution, diffusion and impact of IT fashions on companies. Dos Santos and Pfeffers (1995) demonstrated that the very early engagement in new IT can add over proportional value. Hoppe (2000) showed that under certain conditions, even second mover strategies can be advantageous due to spillover effects. Lu and Ramamurthy (2010) examined different strategies in stable and dynamic environments and showed general support for the assumption that proactive IT innovation leaders outperform reactive IT innovators in overall performance, allocation and cost efficiency. Wang (2010) found that companies that invested in fashionable IT innovations gained a better reputation and improved their performance due to over proportional returns resulting from competitive advantages in the long term. Though all this research provides valuable insights into the advantageousness of engagement in fashionable IT innovations, it stays on a rather generic level without explicitly examining how the idiosyncrasies of fashionable IT innovations might affect the optimal engagement. However, in particular the consideration of a fashionable IT innovation's risk of getting stranded plays a central role as those investments either can "[...] fail to produce the expected benefits, or indeed, any benefits at all" or "[...] could produce some benefits, but not enough to recover the costs of implementation" (Fichman 2004a). As one of the few, Kauffman and Li (2005) address this challenge and by applying a real options approach argue that within their parameterization, technology adopters are better off by deferring investments until the technology's probability to become widely accepted reaches a critical threshold of approx. 60%. The approach of Häckel et al. (2013) examines the error that occurs from applying fixed strategies regarding the investment in fashionable IT innovations. However, their approach is limited to a two period-dynamic optimization and also neglects organizational learning which is substantial for our analysis.

Only very few literature addresses the effect of organizational learning on a company's individual innovator profile and thus on the engagement in fashionable IT investments. As an example, previous research by Stratopoulos and Lim (2010) found that for becoming a systematic innovator who outperforms competitors, persistence and learning regarding the engagement in new emerging IT innovation is inevitable. Due to continuous learning, systematic innovators have more experience in selecting and implementing IT which is still in a fashionable phase but eventually appropriate for the company, as well as in evaluating new applications in the company's context (Swanson and Ramiller 2004). Thus, IT fashion investments not only depend on the acceptance of the technology by a broad range of companies but also on the effect of organizational learning through a continuous engagement which improves the company's ability to innovate with new IT. This ability also can be described as the company's individual innovator profile (Fichman 2004a). Barua and Kriebel (1995) found that those companies which are more efficient in utilizing investments in IT are more likely to be aggressive regarding IT investments and thus probably also with regard to their engagement in fashionable IT innovations. Thus, innovating with new emerging IT requires continuous learning to bridge the gap between existing knowledge, experience, as well as abilities and those aspects that a new emerging IT innovation requires companies to know (Fichman and Kemerer 1997; Weiling and Kwok Kee 2006).

Organizational Learning Regarding IT Innovation Investments

Swanson and Ramiller (2004) describe four core phases of the IT innovation engagement, namely *comprehension*, *adoption*, *implementation* and *assimilation*. In the *comprehension phase* a company has to learn about the IT innovation's intent and why it makes sense to adopt it. The subsequent *adoption phase* requires a solid assessment of the IT innovation's purpose, its benefits, and technical features. In this phase also the business case which accompanies the IT innovation has to be evaluated. Throughout the *implementation phase* the company has to identify its capabilities which are required to arrange the IT innovation in the company-specific context. Additionally, this requires employee's acceptance and training and, possibly, modifications of the innovation. In the *assimilation phase* the IT innovation has to be integrated into the daily business and has to be thoroughly understood to make it productive (Wang and Ramiller 2009). Looking at fashionable IT innovations, which - by nature - are characterized by high immaturity and a lack of thorough understanding or best practices, a well-founded process of comprehension, adoption, implementation and assimilation is a challenging task. Hence, organizational learning and extensive experience are particularly crucial to the outcome of the engagement in fashionable IT innovations as the introduction of new emerging technologies imposes "[...] a substantial burden on the adopter in terms of the knowledge needed to understand and use them effectively" (Weiling and Kwok Kee 2006). Certainly, the engagement in mature IT innovations also requires experience and benefits from organizational learning. However, since a lack of experience in comprehension, adoption, implementation or assimilation regarding mature IT innovations can largely be compensated by, for example, existing best practices or experiences of other companies, this paper's organizational learning analysis focuses on the ability to innovate with fashionable IT (for example through carrying out successful or unsuccessful projects (Caron et al. 1994)). Various literature sources have found that organizational learning affects a company's individual innovator profile and thus improves its ability to comprehend, adopt, implement, and assimilate IT innovations successfully (Ashworth et al. 2004; Fichman and Kemerer 1997; Salaway 1987; Wang and Ramiller 2009). As learning through engagement in IT innovations improves a company's overall performance from innovating with IT (Tippins and Sohi 2003), the examination of how organizational learning affects the theoretically optimal engagement in fashionable IT innovations is highly important. Previous research - either empirically or qualitatively - emphasized that learning aspects in an IT innovation engagement, learning through experiments, and persistence in innovating are important for increasing the ability to innovate with IT (Lucas et al. 2007; Stratopoulos and Lim 2010; Swanson and Ramiller 2004; Wang and Ramiller 2009). To measure the outcome of organizational learning, previous organizational and IT innovation literature applied learning curves which describe the development of a company's ability to innovate (Ashworth et al. 2004; Epple et al. 1991; Robey et al. 2000). As learning can result from both, negative and positive experience (Caron et al. 1994), it is well accepted that making the experience is important "[...] even if some of that "knowledge" subsequently proves, with growing experience, to be false" (Wang and Ramiller 2009).

However, though we see a rich empirical and qualitative literature that deals with organizational learning in the context of IT innovation investments, formal-deductive and mathematical models incorporating

learning aspects in the evaluation of the engagement in fashionable IT innovations are virtually absent. This paper aims at contributing to this research gap by transferring findings from previous literature to a formal-deductive mathematical model which incorporates the effect of organizational learning on a company's individual innovator profile and thus the optimal engagement in fashionable IT innovations. By doing that, the model aims at providing hypotheses that can be tested empirically afterwards. Our model's scope is to analyze how organizational learning and a fashionable IT innovation's probability of success affect the theoretically optimal engagement in mature and fashionable IT innovations. However, companies in practice usually cannot calculate such an optimal engagement exactly and thus rather apply fixed investment strategies as emphasized by Ross and Beath (2002) or Nagij and Tuff (2012). Hence, we in a second step analyze the potential error that stems from applying such fixed investment strategies by particularly focusing on the influence of a fashionable IT innovation's probability of success as well as a company's individual innovator profile.

Towards an optimal IT innovation investment strategy considering fashionable technologies and organizational learning

In accordance with the design-science research guidelines by Hevner et al. (2004) as well as Gregor and Hevner (2013) we in the following develop our artifact, a dynamic optimization model for determining the optimal allocation of a periodical IT innovation budget to mature and fashionable IT innovations. We then take this model's result to derive theoretical propositions on how organizational learning and a fashionable IT innovation's probability of success affect the engagement in fashionable IT innovations. According to Hevner et al. (2004), mathematical models are a common approach to represent an artifact in a structured and formalized way. For the evaluation, we in a second step combine an experimental and a descriptive design evaluation method which is a widely used approach for evaluating artifacts based on mathematical models (e.g., Wacker (1998)).

The Model

Our analysis' focus is on the IT innovation portfolio of a company whose strategic IT innovation investments are regularly re-allocated. In every point of time t , the company decides how to allocate a periodical IT innovation budget (ITIB) to two different types of IT innovations (*mature* IT innovations vs. *fashionable* IT innovations) to maximize its expected cash flows over the planning horizon. The investment opportunities are clustered in these two major categories according to their discourse, diffusion, popularity and maturity (Tsui et al. 2009; Wang 2009).

A) Mature IT innovations: IT innovations that, according to the concept of hype cycles already reached an evolution between slope of enlightenment and plateau of productivity (Fenn and Raskino 2008) or according to Roger's (2003) theory already are adopted by a significant amount of the market but lack mass adoption. As their evolution can be roughly estimated, no early mover advantage can be realized any more as the competitive advantage is too low due to the reached maturity. Examples for mature IT innovations that in an earlier stage experienced a fashionable phase are Customer Relationship Management (CRM) or Enterprise Resource Planning (ERP) (Wang 2010).

B) Fashionable IT innovations: IT innovations that, according to the concept of hype cycles, are in an evolutionary phase between technology trigger and trough of disillusionment and thereby fashionable (Fenn and Raskino 2008; Wang 2010). Though their long-term evolution is unclear, they are accompanied by a hype through a fashion-setting network. An engagement promises competitive first mover advantages in case of wide adoption and institutionalization. However, the technology's immaturity makes estimations about a future evolution difficult as the hype might fade away without reaching a long-term productivity. Regarding today's situation of discourse in research and practice, we can state emerging IT innovations like 3D Printing or Near-Field-Communication (NFC) technologies as fashionable IT innovations (Gartner 2012; Wang 2010).

As both types of IT innovations bear severe risks as well as tremendous opportunities, companies are well advised by incorporating future developments and consequences into their initial decision as to how much and when to invest in which kind of suitable IT innovation in order to innovate mindfully (Swanson and Ramiller 2004). Thus, to avoid gut feeling investments, methodically rigor models with initially reasonable results are needed, although they might have to be adjusted to suit the requirements of real

world investment problem settings. Due to that reason, Hevner et al. (2004) argue that - in the context of design-science research - the overemphasis on rigor can lessen relevance and that both paradigms, rigor and relevance, have to be relevant for all IS related research. For this reason, we need assumptions that cover crucial parts of our real world investment problem setting.

Assumptions and Objective Function

Assumption 1: A company's IT department (in the following we do not differentiate between the IT department of a company and the company itself) invests a periodical, constant IT innovation budget ITIB at points in time $t = 0, 1, \dots, n$, each for one period. We define $a_t^F \in [0,1]$ as the share of ITIB that is invested in fashionable IT innovations (F) at t . Since companies naturally do not spend their whole IT innovation investment budget on fashionable IT innovations due to a conservative investment strategy that aims at optimizing existing products (Hoppe 2000; Lu and Ramamurthy 2010), we define $a_t^N = 1 - a_t^F \geq 0$ as the share of ITIB that is invested in mature IT innovations (N).

The allocation of an IT innovation portfolio's budget to different types of IT innovations thereby follows Ravichandran and Liu (2011), who state that a company's IT investment strategy refers to its "[...] strategic orientation toward IT investing in terms of scale and proactiveness". Thus, we model the scale in terms of the share allocated to fashionable and mature IT innovations, respectively. One additional fact which is more important to our research is that we also include proactiveness in terms of a company's "[...] attitude toward technology adoption [...]" (Ravichandran and Liu 2011) by differentiating between IT innovations with different maturities and potential risks. Figure 1 shows the split of ITIB into the two investment alternatives F and N.

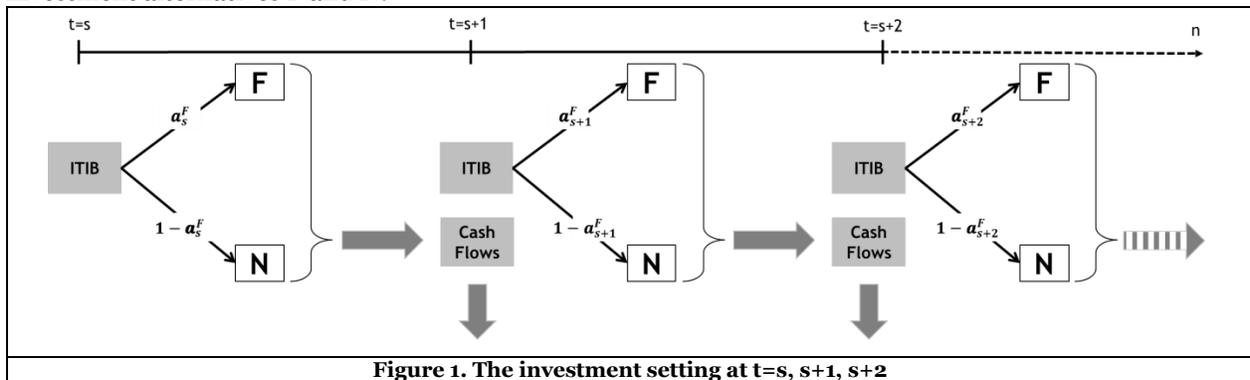


Figure 1. The investment setting at $t=s, s+1, s+2$

Assumption 2: The IT innovation portfolio's cash flows CF_t^{PF} consist of the investment's cash flows CF_t^F resulting from the fashionable IT innovation investment and the cash flows CF_t^N resulting from the mature IT innovation investment.

$$CF_t^{PF} = CF_t^F + CF_t^N \text{ with } t \in \{1, 2, \dots, n\}$$

As a result, the investment alternatives 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. To model the idiosyncrasies of the investment setting in more detail, we take a closer look at the cash flows that are realized by N and F.

Assumption 3: 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:

$$CF_t^i(a_{t-1}^i) = (a_{t-1}^i \cdot ITIB)^{q_z^i} \cdot v_{t-1}^i \text{ with } q_z^i \in [0,1), v_{t-1}^i \in R^+, i \in \{N, F\}, z \in \{u, d\}$$

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 understanding and a broader implementation of the technology possible and therefore provides more opportunities to create value out of the investment later on (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 production theory (Varian 1999). Hence, a first engagement in IT innovation creates more value than the additional increase of an already quite high

investment as the initial engagement enables entering a market or becoming reasonably familiar with a technology (Lu and Ramamurthy 2010; Stratopoulos and Lim 2010). Moreover, due to the diminishing marginal utility of the cash flow function, a very high investment in fashionable IT innovations is not unlimited beneficial. Given that at some point the cash flow falls below the investment budget $ITIB$ which is depicted by the diminishing marginal utility, the company's engagement leads to a negative sum of $ITIB$ and the cash flows of the fashionable IT innovation even if the latter is institutionalized and accepted by the market. Thus, a pure "more is better" approach might not hold true for every IT innovation investment. Furthermore, even though the cash flow function is monotonically increasing, the cash flow is limited by the limited IT innovation budget $ITIB$. Another possible way of modeling the cash flows would be a step function as certain investments require a minimum engagement (that has to go beyond an initial pilot investment which often is applied to test new emerging technologies). This would mean that a marginally increased engagement would not increase the cash flows at all as the IT innovation's next stage of expansion would require a distinctively higher engagement. However, as a step function requires the modeling of fixed investment levels as constraints which are even hard to specify in practice, we find applying a smooth cash flow function as modeled above as reasonable.

The factor q_z^i with $i \in \{N, F\}$ and $z \in \{u, d\}$ that is constant over time can be interpreted as a technology-specific impact factor describing the impact degree of N and F, i.e., the IT innovation's general acceptance by customers or employees, its stability, or the probability of an easy integration into the company's existing IT infrastructure, etc., that influences the investment's cash flow (Fichman 2004b; 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 (Lu and Ramamurthy 2010; Wang 2010), we assume F's technology factor q_z^F with $z \in \{u, d\}$ to be generally higher than N's q_z^N with $z \in \{u, d\}$, i.e., $q_z^F > q_z^N \forall t = 1, \dots, n$ with $z \in \{u, d\}$. However, as an IT innovation's impact on the market is difficult to predict, both scenarios, a high impact ("upside" with $z = u$) and a low impact ("downside" with $z = d$), have to be considered (Fenn and Raskino 2008). Whereas upside scenarios regarding an IT innovation for example can be interpreted as high acceptance by customers or employees leading to higher cash flows or institutionalization in the first place (especially for fashionable IT innovations), a downside scenario for example can be characterized by difficulties within the integration in existing processes or even the case of getting stranded (in the case of fashionable IT innovations). Therefore, we model an upside scenario as well as a downside scenario for N and F into the technology-specific impact factor, i.e., $q_u^i > q_d^i \forall t = 1, \dots, n$ with $i \in \{N, F\}$, and by that incorporate uncertainty about the IT innovation's possible outcome. Thereby, cases where the mature IT innovation in a positive scenario might have a higher impact than the fashionable IT innovation in a negative scenario, i.e. $q_d^F < q_u^N$, are possible. Though modeling only "positive" or "negative" scenarios is a rather binary view and simplifies real world scenarios that might lie somewhere in between, it incorporates the borderline cases which are of high relevance for this analysis.

The factor $v_{t-1}^i \in R^+$ with $i \in \{N, F\}$ can be interpreted as the company's individual innovator profile at t regarding mature IT investments (N) or fashionable IT investments (F). Hence, this factor generally describes the company's ability to engage in an IT innovation economically, quickly and efficiently (Fichman 2004a; Swanson and Ramiller 2004). To make an easier interpretation of the innovator profile v_t^i with $i \in \{N, F\}$ possible, we level a company that is average innovative (compared to the market) at the point in time t with $v_t^{i*} \in R^+$, below-average innovative with $v_t^i < v_t^{i*}$, and above-average innovative, i.e., first and progressive movers, with $v_t^i > v_t^{i*}$, in order to transfer empirical findings by Stratopoulos and Lim (2010) as well as Lu and Ramamurthy (2010) to an analytical model. Thus, in our presented approach the individual innovator profile always depicts a company's innovativeness in comparison to the market average which suits the usually intense competition in dynamic and technology driven market environments (Lu and Ramamurthy (2010). As existing literature (Nagji and Tuff 2012; Stratopoulos and Lim 2010; Wang and Ramiller 2009) puts emphasis on the fact that a steady engagement in *new emerging IT* is important for a company's innovativeness and for continuous learning as well as the fact that *experiments* are mostly the source of transformational innovation, *our analysis of learning focuses on the engagement in fashionable IT innovations*. This focus is reasonable as, in contrast to mature IT innovations, fashionable IT innovations require a substantially higher level of experience in comprehending, adopting, implementing and assimilating new IT due to their immaturity and lack of thorough understanding and best practices. Consequently, we can narrow our analysis down to the effect of organizational learning on the company's individual innovator profile regarding fashionable

IT innovations. For reasons of simplicity we assume the individual innovator profile regarding mature IT investments v_t^N to be constant over time.

Summarizing, both factors, the technology specific impact factor q_z^i with $i \in \{N, F\}$ and $z \in \{u, d\}$ as well as the company's individual innovator profile indicator factor $v_{t-1}^i \in R^+$ with $i \in \{N, F\}$ consolidate a variety of different factors. Certainly, these factors again can be split up in several sub-dimensions that might be addressed in further research. However, as we focus on a more general level and to keep the balance between rigorousness and interpretability, simplifying from reality is reasonable in this case.

Assumption 4: *The development of a company's individual innovator profile regarding fashionable IT investments v_t^F follows a learning (by doing) curve in form of a s-curve which depends on a_{t-1}^F :*

$$v_t^F = v_{t-1}^F \cdot M_{t-1}(a_{t-1}^F) = v_{t-1}^F \cdot \left((1 - \beta) + \frac{2 \cdot \beta}{1 + \exp(-k \cdot (a_{t-1}^F - \alpha^F))} \right)$$

Though learning curves are an accepted phenomenon in IT innovation literature (Ashworth et al. 2004; Robey et al. 2000), the fact that measuring organizational learning exactly is virtually impossible or at least very demanding has generated various different ways of modeling the increase in knowledge over time. Whereas, for example, Wang and Ramiller (2009) focus on community learning, we model a *learning by doing* (i.e., engagement in fashionable IT innovations) relation which is analogous to approaches where the required labor per produced unit decreases with an increase in production (Epple et al. 1991). This means that a company experiences organizational learning through engagement in fashionable IT innovation in terms of gaining experience during the comprehension, adoption, implementation and assimilation of such a new emerging technology. Regardless of whether the fashionable IT innovation later becomes institutionalized or not, the company improves its individual innovator profile as, for the next time, it might be able to better assess, select and implement another fashionable IT innovation due to former experience. Of course, this is simplifying matter as one cannot guarantee that the (probably bad) experience made with one technology is always helpful for future investments. Thus, in case of technical leaps the previous learning about technological details might become useless for another technology. Therefore, in practice not every engagement in a fashionable IT innovation involves organizational learning as especially new emerging technologies often are very different from each other which might constrain the full spillover effect of organizational learning between different investments. Though our model implicitly assumes such a full spillover effect between all fashionable IT innovations, we at this point find it appropriate to simplify from reality to limit complexity and due to the fact that up to a certain degree, all kind of experience is useful for a later engagement. This also is supported by previous literature which emphasizes that companies require steady engagement in new emerging technologies to stay at the forefront of innovativeness (Nagji and Tuff 2012; Stratopoulos and Lim 2010; Wang and Ramiller 2009). Therefore, we model the development of a company's individual innovator profile regarding fashionable IT innovations and thus its ability to innovate with fashionable IT in the form of a s-curve (Kemerer 1992; Raccoon 1996) as this type is the most suitable one to depict the increasing but somehow limited ability to innovate with IT. Our specific learning curve is based on the well-known logistic function and adjusted to our particular requirements. As we measure v_t^F in comparison to the market average, the included shift assumes a competition-based learning which depends on the market's average engagement in fashionable IT innovations α^F . This modeling ensures that a company can increase its innovator profile regarding fashionable IT investments relative to the market only if it invests more in fashionable IT than the market's average does, i.e., $a_{t-1}^F > \alpha^F$. Consequently, the company's individual innovator profile decreases relative to the market in case its engagement is lower than the market average α^F , although the company might realize organizational learning through its engagement in fashionable IT innovations. Though this might not be intuitive on a first view, it is reasonable as a company might be innovative from its isolated view with a (subjectively) high engagement in new emerging technology but compared to a market which engages even more might be a rather below-innovative company. In this case, it is difficult for a company to keep pace with the market even though it finds itself very innovative. Thus, the incorporation of the market's innovativeness is important as Stratopoulos and Lim (2010) argue that for staying a systematic innovative company that outperforms the market through innovating with IT, a company requires a substantial difference in its IT innovation activities compared to the competitors. The growth rate β thereby specifies the maximal periodical increase respectively decrease in the innovator profile generated by the learning effect. The proportionality factor k is an indicator how sharply the curve increases and therefore how

strongly the difference between the company's investment level and the market average influences the learning effect. Thus, the learning curve depends on the extent of the engagement in fashionable IT (regardless of whether they will be successful or not) (Caron et al. 1994). In addition to the learning curve we restrict the innovator profile to a global upper limit G . In reality, the company will - at some point - reach a level of saturation of innovativeness, which impedes the possibility to gain infinite knowledge and innovativeness. A reasonable value for G might be two times the average market innovator profile $v_t^{F^*}$. To sum up, our approach of modeling organizational learning certainly simplifies from reality and inherits the assumption that engaging in fashionable IT innovations simply increases organizational learning. However, as our model aims at providing first propositions which later can be tested empirically rather than a one-to-one application to real-world business problems, modeling the development of a company's innovator profile in this way seems appropriate for the purpose of this paper.

Assumption 5: *The IT innovation's lifecycle - as described above - is broken down and modeled as a time frame including two periods whereas $t = s$ describes the point of time when a fashionable IT innovation emerges (i.e., technology trigger, peak of inflated expectations and trough of disillusionment) and $t = s + 1$ describes the point of time when its destiny turns out (slope of enlightenment with institutionalization or failing). Consequently, in case that a fashionable IT innovation becomes institutionalized (=mature), $t = s + 2$ describes its plateau of productivity's altitude. In case of a mature IT innovation, the time frame illustrates its impact over two periods. As fashionable and mature IT innovations recur constantly over time, we assume that the described time frame and the scenarios for the fashionable and mature IT investments repeat every two periods.*

Breaking an IT innovation's lifecycle down into a recurring time frame including two periods definitely simplifies the matter but allows us to analyze a longer time frame of subsequent decisions regarding the allocation to mature and fashionable IT innovations. Thus, we analyze a company's IT innovation investment strategy over a longer time frame by focusing on two periods which are sufficient to schematically model the most crucial idiosyncrasies of the investment problem setting as in this phase an IT innovation is "in fashion" (Wang 2010). In addition, limiting the time frame to two periods makes it possible to keep the mathematical model as simple as possible by not limiting the central propositions for research and practice at the same time.

Assumption 6: *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 $i \in \{N, F\}$ 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 $i \in \{N, F\}$ via a binomial distribution.*

Though different fashionable IT innovations in reality are likely to be characterized by different probabilities regarding institutionalization, we for reasons of simplicity assume the probabilities p^i with $i \in \{N, F\}$ to be constant over time. However, as constant probabilities do not disturb the general results of our model and varying probabilities might only pretend improved accuracy of measurement, constant probabilities as assumed are justifiable. Hence, p^i with $i \in \{N, F\}$ describes the possibility that an investment in N creates the desired cash flows (N^u with q_u^N) at $t = s + 1$ and $t = s + 2$ respectively, or, in case of F, becomes institutionalized at all at $t = s + 1$ and creates desirable cash flows at $t = s + 2$ (F^u with q_u^F). By means of $1 - p^i$ with $i \in \{N, F\}$ we describe the probability that an investment in N will create below-average cash flows (N^d with q_d^N) at $t = s + 1$ and $t = s + 2$ respectively or, in case of F, will turn out to be a failing technology at $t = s + 1$ with $CF_t^F = 0$. In case F became institutionalized at $t = s + 1$, $1 - p^F$ represents the probability that F will create below-average cash flows at $t = s + 2$ (F^d with q_d^F).

IT fashion literature assumes companies to engage in fashionable IT innovations due to two major reasons: Whereas the economic-rationalistic perspective focuses on the organizational performance in terms of financial returns, the institutional perspective stresses organizational legitimacy reasons as an important factor (e.g., pressure of other companies) (Wang 2010). As our approach aims at providing insights that avoid an engagement in fashionable IT innovations on a gut feeling, we focus on the first perspective and thus financial aspects as key decision criteria which is depicted in the following assumption.

Assumption 7: 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 $E(CF_t^{PF})$. The expected cash flows are discounted to present with a risk-free interest rate $r \in [0,1]$ that is assumed to be constant for each period.

Assuming a risk neutral decision maker who decides on the basis of the expected value of a company's IT innovation portfolio is reasonable as the IT innovation portfolio's scope is to do basis research for discovering long-term value. 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 and Handler 2005; Ross and Beath 2002). Assuming a risk-averse decision maker is due to further research regarding the question of how the explicit consideration of the risk/return trade-off affects the engagement in fashionable and mature IT innovations. However, we do not expect the general cause-and-effect relationships among the crucial factors to change distinctively in a model that considers a risk-averse investor.

Cash Flows at t: A fashionable IT innovation can turn out to be both, a failing technology (i.e., a downside scenario with q_d^F even leads to zero cash flows at $t = s + 1$) and a groundbreaking technology (i.e., an upside scenario with q_u^F results in extraordinary high cash flows for early movers). Therefore, its cash flows at $t = s + 1$ and $t = s + 2$, after the hype around the technology has waned, are of particular interest to the analysis (Fenn and Raskino 2008; Fichman 2004a). Regarding the mature IT innovation we also have to consider a downside as well as an upside scenario. According to our assumptions, investing in a fashionable IT innovation F or a mature IT innovation N at $t = s$ can result in the following cash flows CF_t^F or CF_t^N with $t = s + 1$ and $t = s + 2$:

Table 1. Scenarios for the IT innovation's cash flow			
		t = s + 1	t = s + 2
Upside scenario (p^i) with $i \in \{N, F\}$	F	$(a_s^F \cdot ITIB)^{q_u^F} \cdot v_s^F$	$(a_{s+1}^F \cdot ITIB)^{q_u^F} \cdot v_{s+1}^F$
	N	$(a_s^N \cdot ITIB)^{q_u^N} \cdot v_s^N$	$(a_{s+1}^N \cdot ITIB)^{q_u^N} \cdot v_{s+1}^N$
Downside scenario ($1 - p^i$) with $i \in \{N, F\}$	F	0	$(a_{s+1}^F \cdot ITIB)^{q_d^F} \cdot v_{s+1}^F$
	N	$(a_s^N \cdot ITIB)^{q_d^N} \cdot v_s^N$	$(a_{s+1}^N \cdot ITIB)^{q_d^N} \cdot v_{s+1}^N$

To enable an ex ante analysis on how the engagement in fashionable IT innovations (i.e., the allocation of the IT innovation budget $ITIB$ at t to fashionable IT innovations) is affected by organizational learning and the probability of success, we determine the allocation of $ITIB$ that maximizes the IT innovation portfolio's expected net present value (NPV). Hence, the objective function of the dynamic optimization problem is as follows:

$$\max_{a_t^F} \sum_{t=0}^n \frac{-ITIB + E(CF_t^{PF})}{(1+r)^t} \quad s. t.$$

$$0 \leq a_t^F \leq 1 \text{ and } v_t^F = v_{t-1}^F \cdot M_{t-1}(a_{t-1}^F)$$

Model Evaluation

We solve this dynamic optimization problem on the basis of a decision tree with the different scenarios regarding the evolution of F and N and perform a roll-back (i.e., dynamic programming according to Bellman (1957)) analysis (Clemons and Weber 1990; Magee 1964; Suleyman 1993). For the evaluation we choose a planning horizon of ten periods (comprising five innovation lifetime cycles with two periods each) as this makes it possible to perform a meaningful analysis of the organizational learning effect's influence by ensuring reasonable simulation runtimes at the same time. A major advantage of this decision-tree based roll-back analysis is that its primary focus is on the investment decisions that have to be made, the incorporation of interrelationships between variables, and the optimization over the possible decisions (Bonini 1975). A real option approach as applied by Kauffman and Li (2005) or Fichman (2004) might also have been suitable to address this decision setting but inherits restrictive assumptions as the existence of a twin security, and so is not suitable for an ex ante allocation of an IT Innovation budget. Though acquiring real world data to examine the benefits of our theoretic approach profoundly is rather

difficult, considerable advantages for the evaluation can be realized when knowing how the engagement in fashionable IT innovations might be affected by various factors. According to Hevner et al. (2004) as well as Gregor and Hevner (2013), the analytical evaluation of an optimization model or the gathering of data by simulation are legitimate means in IS research. Table 2 shows the simulation's parameter ranges which are relevant for the simulation. For the sake of simplicity we assume equal distributions for all parameters as other distributions, such as the Gaussian, would not distort the general conclusions but increase complexity. Analogous to Kauffman and Li (2005) we take $r = 0.1$ for the risk-free interest rate and $v_t^{N*} = 100$ for the company's individual innovator profile regarding mature investments. 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. To demonstrate the impact of organizational learning on investment evaluation regarding fashionable IT innovations, our simulations generally include a comparison between the optimal IT innovation budget's allocation resulting from the model *with learning effect* to the model *without learning effect*. Additionally, we analyze the potential error that occurs from deviating from the theoretical optimum by applying a fixed investment strategy.

Parameter	Range
Company's individual innovator profile v_0^F	50 – 150
Fashionable IT innovation's impact factor q_u^F (upside scenario)	0.25 – 0.50
Mature IT innovation's impact factor q_u^N (upside scenario)	0.20 – 0.40
Probability that fashionable IT innovation will create desirable cash flows p^F	0.05 – 0.15
Probability that mature IT innovation will create desirable cash flows p^N	0.15 – 0.30
Average engagement of the market α^F	0.05 – 0.15

The impact of a company's initial innovativeness v_0^F on the optimal investment strategy

In the first place, we simulate 500 different scenarios and analyze the average optimal investment strategy for a below-average innovative company (with $v_0^F = 50$), an average innovative company (with $v_0^F = 100$) and an above-average innovative company (with $v_0^F = 150$). Given this parameter setting and the justifiable assumptions mentioned above, our first proposition is that the optimal engagement a_t^F in fashionable IT innovations increases with the company's innovativeness and changes dynamically over time as shown in Figure 2. Within this setting, we observe that a below-average innovative company which aims at maximizing the expected NPV can reach this by slowly increasing the engagement in fashionable IT innovations over time. This can be explained by organizational learning through engagement in fashionable IT innovations which improves the future ability to innovate with IT. We observe a similar situation for an average innovative company except that the range of 16.58% between the lowest and the highest value for a_t^F over time substantially exceeds the range of 7.55% for a below-average innovative company. Thus, we assume that an average innovative company might clearly benefit from organizational learning resulting in a distinct increase of the engagement in fashionable IT innovations over time. In contrast, our analysis reveals that the investment strategy of a below-average innovative company does change less over time compared to the investment strategy of an above-average or average innovative company as it will hardly reach the innovativeness of the market average despite the positive effects of organizational learning. Regarding an above-average innovative company, we observe an engagement which increases in early points of time as seen for an average innovative company. However, it levels off at a constant level as soon as the maximal and limited innovativeness is reached. Consequently, the range of 10.57% regarding the development of a_t^F over time shrinks compared to the range for an average innovative company but still exceeds the range for a below-average company.

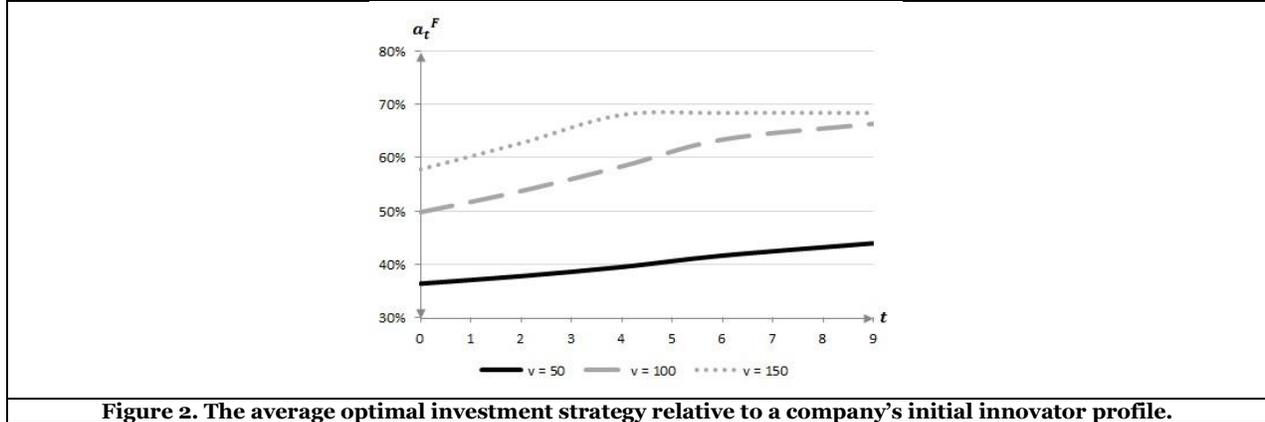


Figure 2. The average optimal investment strategy relative to a company's initial innovator profile.

Within this analysis, an average innovative company dynamically adjusts its engagement in fashionable IT due to organizational learning. Furthermore, a below-average innovative company is considerably less affected by organizational learning and therefore also the optimal investment strategy is rather fixed over time. We also notice that an above-average innovative company scales its engagement at first, but sooner or later changes to a constantly high investment strategy and keeps it fixed over time. Though our model enables us to determine an optimal ex ante IT innovation investment strategy from a theoretical point of view, companies in practice should individually select IT innovations regarding the appropriateness to the company (Swanson and Ramiller 2004).

Additionally, individual company profiles, high estimation uncertainty regarding model parameters or political reasons might impede a direct transfer to real world business decisions. This in practice often leads to fixed IT innovation investment strategies for different kinds of (IT) innovations for different industries (Nagji and Tuff 2012; Ross and Beath 2002). However, such fixed strategies that are comparable to naive rules of diversification in financial portfolio theory by nature differ from the company's individual optimal investment strategy and in particular do not consider the effect of organizational learning. Taking our model, for each simulation run i with $i \in \{1, \dots, 500\}$ we can determine the evaluation error $\Delta_{i,j}^{err}$ by comparing the IT innovation portfolio's optimal NPV_i^{opt} with the $NPV_{i,j}^{fix}$ that results from applying a certain fixed investment strategy j (i.e., j represents one possible fixed combination of allocating the IT innovation budget with e.g., $a_t^F = 40\%$ and $a_t^N = 60\%$):

$$\Delta_{i,j}^{err} = \frac{NPV_i^{opt} - NPV_{i,j}^{fix}}{NPV_i^{opt}}$$

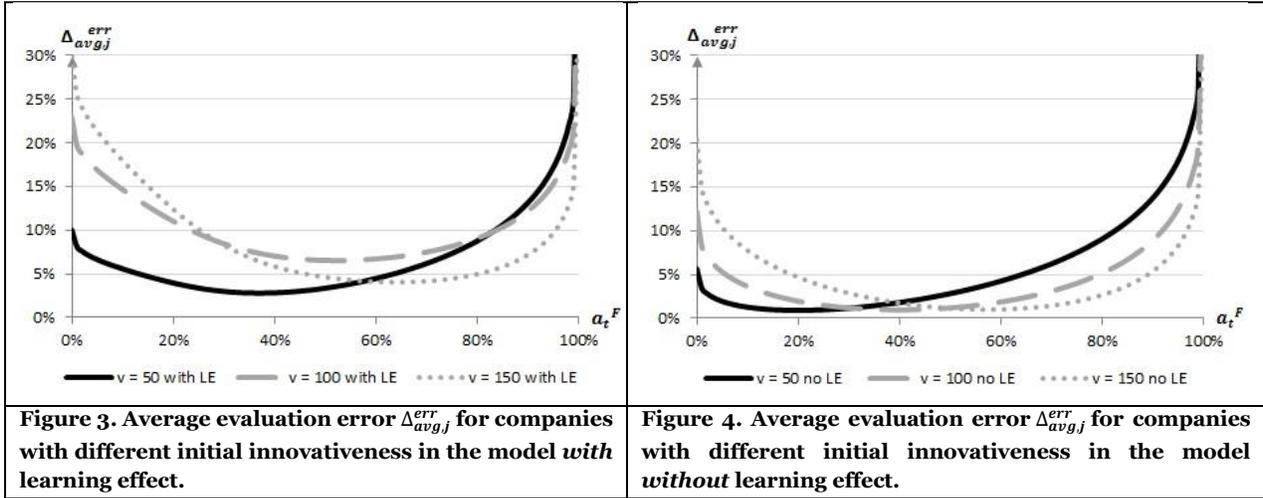
To examine the extent of the evaluation error, we change the engagement a_t^F and so obtain different fixed strategies j . For every fixed strategy j , we calculate the *average evaluation error* $\Delta_{avg,j}^{err}$:

$$\Delta_{avg,j}^{err} = \frac{1}{500} \cdot \sum_{i=1}^{500} \Delta_{i,j}^{err}$$

In the following, we illustrate $\Delta_{avg,j}^{err}$ depending on the engagement in fashionable IT Innovations, i.e., the potential economic error that arises from applying a fixed strategy regarding the allocation of an IT innovation budget to fashionable IT innovations (as we only consider two investment alternatives, a fixed engagement a_t^F at once determines the engagement a_t^N in mature IT innovations). In a first step, we examine the impact of a company's initial innovativeness on the potential error that occurs from applying a fixed investment strategy regarding fashionable IT innovations. For that, we calculate the average evaluation error for an initially below-average innovative company (with $v_0^F = 50$), an initially average innovative company (with $v_0^F = 100$) and an initially above-average innovative company (with $v_0^F = 150$). In another simulation we aim at examining the impact of a fashionable IT innovation's probability of success on the potential error that occurs from applying a fixed investment strategy regarding fashionable IT innovations. For that, we assume an average innovative company with $v_0^F = 100$ and calculate the average evaluation error that arises in scenarios with a probability of success for a fashionable IT innovation of $p^F = 5\%$, $p^F = 10\%$, and $p^F = 15\%$. To illustrate the effect of organizational learning, we additionally repeat all the described simulations and analyses for the same model setting *without* the effect of organizational learning and compare the results.

The impact of a company’s initial innovativeness v_0^F on the potential error from fixed investment strategies

As might be expected, a company’s initial innovator profile v_0^F not only affects the optimal allocation of an IT innovation budget to fashionable IT innovations but also the evaluation error that occurs from applying a fixed investment strategy regarding fashionable IT innovations. In Figure 3 we illustrate the average evaluation error $\Delta_{avg,j}^{err}$ for all possible fixed investment strategies regarding fashionable IT innovations for companies with different initial innovativeness in a model with organizational learning. Figure 4 illustrates $\Delta_{avg,j}^{err}$ in a model without organizational learning.



The global minimum of each curve represents the fixed investment strategy j^* where the average evaluation error is minimal. Regardless whether we apply a model with or without considering the effect of organizational learning, the results of our analysis which we can observe in Figure 3 and Figure 4 let us assume that companies with a higher initial innovativeness are better off by allocating a higher fixed share of their IT innovation budget to fashionable IT innovations than companies with a lower initial innovativeness. This is illustrated by the fact that for companies with higher initial innovativeness the minimal average evaluation error occurs at a higher fixed engagement j . As we focus on only two types of IT innovations (mature and fashionable) and also consider the effect of organizational learning, our analysis which results in allocating approx. 50% to fashionable IT innovations for an average innovative company cannot be matched with the results from former literature (Nagji and Tuff 2012; Ross and Beath 2002) which found that allocating about 15% in fashionable IT innovations seems reasonable. However, previous literature usually incorporated more than two types of IT innovations and furthermore neglected organizational learning which might explain the considerably lower engagement in fashionable IT innovations. This is underlined by the analysis of the model without considering organizational learning, which shows distinctly lower values compared to the model considering organizational learning (20% vs. 37% for $v_0^F = 50$). This results from the effect of organizational learning as operationalized in our model which encourages companies to increase their engagement in fashionable IT innovations in order to benefit from subsequent investments (Ashworth et al. 2004; Salaway 1987; Wang and Ramiller 2009). Besides, our research approach’s focus is on illustrating important cause-and-effect relationships regarding the factors which influence the engagement in IT innovation investments. Thus, in contrast to previous research within this area (Nagji and Tuff 2012; Ross and Beath 2002), we aim at providing general insights for companies regarding important factors to consider rather than specific values as rule of thumb. Interestingly, the average evaluation error’s absolute extent that arises from the fixed investment strategy with the smallest difference compared to the optimal investment strategy strongly differs with the company’s initial innovativeness. Looking at the three curves from the model with learning effect (Figure 3), we can observe that Δ_{avg,j^*}^{err} varies from 2.79% (for $v_0^F = 50$) to 6.52% (for $v_0^F = 100$). The relatively small error for a below-average innovative company with $\Delta_{avg,j^*}^{err} = 2.79\%$ can be explained by the fact that given our model setting and parameterization, we suggest the optimal investment strategy almost to be fixed over time for such companies as seen in Figure 2. With an initial

average innovativeness of $v_0^F = 100$, the minimal evaluation error in our analysis increases considerably ($\Delta_{avg,j}^{err} = 6.52\%$) as we observe that the optimal investment strategy changes distinctively more over time for these companies. For above-average innovative companies with $v_0^F = 150$, we can observe that the minimal average evaluation error decreases to $\Delta_{avg,j}^{err} = 4.04\%$ compared to the error for average innovative companies. This matches with the results from the first analysis where we showed that the engagement in fashionable IT innovations does not change as much over time for above-average innovative companies.

In the model without learning effect (Figure 4), we observe a minimal average evaluation error which is substantially lower compared to the model with learning effect for all initial innovator profiles and also does not change across the different initial innovator profiles. This results from the fact that in this setting, an engagement in fashionable IT innovations at a certain point of time does not influence the subsequent decisions and thus, the optimization problem is not dynamic anymore. Hence, the fixed investment strategy with the lowest evaluation error at the same time is the theoretical optimum. The minimal *average* evaluation error of approx. 1% is explained by calculating the average over the 500 simulations. However, the smaller minimal average evaluation error compared to a model with organizational learning shows that the optimal investment strategy does not change dynamically over time. This lets us assume that neglecting the effect of organizational learning can lead to a miscalculation of a company's optimal investment strategy.

As allocating the IT innovation budget in a manner so that the average evaluation error compared to a theoretical optimum hits the minimum is rather complex or even impossible, it is highly relevant to know whether an over- or underinvestment compared to the theoretical optimum results in a higher potential error. The results of our model which are illustrated in Figure 3 and Figure 4 show some general trends about the average evaluation error and thus the disadvantageousness of an over- or an underinvestment. Figure 3 lets us assume that over- and underinvestments result in higher evaluation errors compared to the model that does not consider the effect of organizational learning (Figure 4). Hence, we propose that both, over- and underinvestments are equally disadvantageous in a model considering organizational learning.

To sum it up, given the model setting and the parameter values within the simulation, the second part of our analysis makes us assume that in case of neglecting the effect of organizational learning, a fixed investment strategy regarding fashionable IT innovations does not lead to substantially worse results than applying the theoretically optimal investment strategy. This might be reasoned by the fact that calculating the optimal investment strategy while not considering organization learning probably always leads to a fixed investment strategy. However, the consideration of organizational learning - which clearly better illustrates the real world - in our model shows considerably larger differences between the theoretical optimum and a fixed investment strategy. Thus, we propose that according to our model, companies probably are better off by adjusting their IT innovation budget's allocation over time instead of applying a fixed strategy.

The impact of a fashionable IT innovation's probability of success p^F on the potential error from fixed investment strategies

Even the most innovative company with high ability to innovate with new IT likely profits from incorporating the success probabilities of fashionable IT innovations into its investment strategy as we assume them to substantially affect the expected payoff. Thus, we conduct another simulation and analyze the fashionable IT innovation's probability of success as a parameter of major importance and impact. For this analysis, we hold the initial innovator profile constant at the average value of $v_0^F = 100$ (as we observed the highest volatility regarding the dynamic adjustment of the investment strategy and the evaluation error for this parameterization in our first analysis) and calculate the average evaluation error for fixed investment strategies regarding fashionable IT innovations with an extremely low ($p^F = 5\%$), a medium high ($p^F = 10\%$) and a considerably high ($p^F = 15\%$) probability of success in order to analyze the evaluation error. Figure 5 and Figure 6 show the results of the simulation for a model with and model without organizational learning analog to the Figures above.

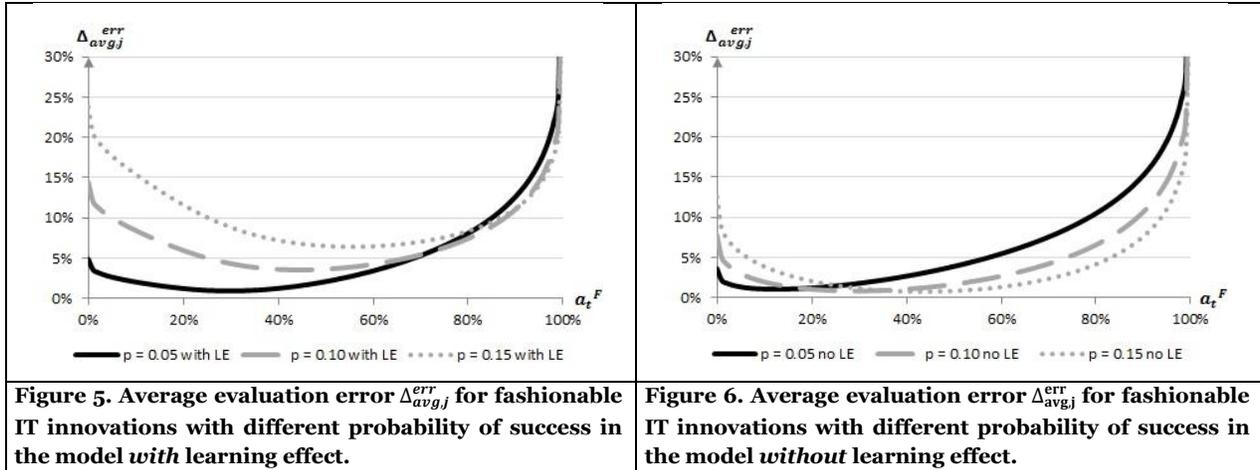


Figure 5. Average evaluation error $\Delta_{avg,j}^{err}$ for fashionable IT innovations with different probability of success in the model *with* learning effect.

Figure 6. Average evaluation error $\Delta_{avg,j}^{err}$ for fashionable IT innovations with different probability of success in the model *without* learning effect.

The curves in Figure 5 show that with a higher probability of success, the average evaluation error that arises from the fixed investment strategy with the lowest deviation from the theoretical optimum increases for the model considering organizational learning. This is reasonable as a high probability of success given our model assumptions implies a higher engagement in fashionable IT innovations and therefore a higher learning effect which as aforementioned leads to a more dynamic optimal investment strategy over time. This dynamically changing strategy with a higher engagement differs more strongly from a strategy that is constant over time. In analogy to the analysis above, our results let us assume over- and underinvestments to be considerably more disadvantageous in a model considering organizational learning. Figure 6 shows the results for the model without learning effect which are very close to the simulation results regarding different initial innovativeness.

To sum it up, the probability of success in our model substantially influences the evaluation error that results from fixed investment strategies which deviate from the theoretical optimal when considering the effect of organizational learning. Also, our results let us assume that the effect of organizational learning has to be considered when deciding on the engagement in fashionable IT innovations. The neglect of organizational learning according to our results might result in time-constant investment strategies which lead to substantially worse results than a theoretical optimum which changes dynamically over time.

Theoretical and Practical Implications and Limitations

Decisions on investments in new emerging IT innovations that are in a hyped phase (=fashionable IT innovations) often do not follow a thorough analysis but rather a gut feeling. In this context, organizational learning plays an important role to improve the company's individual innovator profile and thus the ability to innovate with new emerging IT. Our model aims at providing first insights in how organizational learning and a fashionable IT innovation's probability of success affect investments in fashionable IT innovations. We thus contribute to IT innovation and organizational literature by developing a mathematical model which incorporates issues related to IT innovations (e.g., probability of success, intensity of competition) as well as company characteristics (e.g., ability to innovate, organizational learning). Though in practice, companies usually should look at any IT innovation individually and then mindfully decide on whether it is appropriate to invest, such mathematical models can support the process of selection and evaluation by emphasizing and illustrating crucial cause-and-affect relationships. For that, we develop a dynamic n-periods optimization approach that optimizes the allocation of a periodical IT innovation budget to different types of IT innovation by considering organizational learning. Our analysis shows that there is a theoretical optimum which changes over time and which mainly depends on the fashionable IT innovation's success probability as well as the company's individual innovator profile. However, this theoretical optimal allocation in practice hardly can be implemented due to management's uncertainty, missing data or political reasons. Companies thus often apply fixed rules within IT innovation investment strategies which seem to be suitable but neglect the effect of organizational learning (Nagji and Tuff 2012; Ross and Beath 2002). We in particular examine the evaluation error that stems from applying such fixed strategies which do not incorporate the effect of organizational learning, thus are constant over time and so deviate from the theoretical optimum. Taking our theoretical model

including its justifiable but also arguable assumptions, our analysis method as well as its parameters' value, our results make us suggesting the following propositions as a basis for further research and practice:

- Independently from a company's ability to innovate, the substantial engagement in fashionable IT innovations can be beneficial.
- Depending on a company's initial ability to innovate, the extent of how an optimal engagement in fashionable IT innovations dynamically changes over time, is different. An average innovative company's optimal allocation is likely to adjust the most over time.
- For below-average innovative companies which according to our results have the smallest change of their optimal allocation over time, applying a fixed strategy regarding the allocation of the IT innovation budget and thus deviating from the theoretical optimum results in the smallest evaluation error.
- Neglecting the effect of organizational learning probably leads to a miscalculation of a company's individual optimal investment strategy as the optimal allocation does not change over time. Thus, the evaluation error that stems from applying fixed strategies and thus from an over- or underinvestment compared to the theoretical optimum is higher when considering organizational learning.
- The higher a fashionable IT innovation's probability of success regarding long-term institutionalization, the higher the evaluation error that stems from applying a fixed strategy.

Our model aims at providing first insights and propositions which might be the basis for empirical validation and useful in further research approaches. Thus, we do not provide decision making guidance which is directly transferable to practice. Further research which in a first step empirically validates the described relationships and in a second step operationalizes the findings in a model that allows for concrete decision support thus might deliver valuable support for business problems. For that, the following aspects which are not covered yet by our approach need to be addressed in future research: Though modeling organizational learning via a learning-by-doing approach is suitable to receive first results, the modeling of learning from communities or fashion-setting networks might provide additional insights. Furthermore, empirically testing the model and its parameters as different dimensions of q or v with real world data is due to further research. Also, the model's inherent interpretation of the IT innovation's value is limited to quantifiable components of value. So far, minimum or maximum investments are not considered yet as well as incorporating risk interdependencies between different IT innovations. Our model focuses on the economic-rationalistic perspective, thus is based on financial aspects and for that assumes a risk-neutral decision maker who decides on the basis of expected values. This approach neglects the possibility of IT innovation investments based on legitimacy issues rather than an assessment of risk and return and also does not address risk-averse behavior. A differentiation between certain specific fashionable and mature IT innovations and considering different success probabilities additionally bears potential for further research. Also, companies might engage in fashionable IT innovations to ensure only competitive parity instead of aiming at competitive advantage or first mover advantages which would require a more game-theoretic approach. Also, we simplify by not differentiating between innovation laggards, opportunistic adopters and systematic innovators which might require a more nuanced view on the engagement. Nevertheless, the model provides a basis for companies to gain insights into the characteristics of fashionable IT innovations which might support the evaluation of their IT innovation investment strategy when considering fashionable technologies. Moreover, it is a theoretically sound economic approach which allows further development and provides insights into IT innovation related issues. Grounding on design-science research, it serves as a basis for future research and aims at addressing "[...] important unsolved problems in unique or innovative ways [...]" (Hevner et al. 2004) to contribute to the understanding and improvement of IT fashion research as "[...] IS researchers should be among the leaders, and not just the followers, of fashion" (Baskerville and Myers 2009).

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