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by

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Europäische Union
„Investition in Ihre Zukunft"
Europäischer Fonds für regionale Entwicklung

in: Proceedings of the 21st European Conference on Information Systems, ECIS, Utrecht, Netherlands, June 2013

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THE ERROR OF FIXED STRATEGIES IN IT INNOVATION INVESTMENT DECISIONS

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Abstract

Allocating an IT Innovation budget to technologies in different maturity stages (mature vs. fashionable IT innovations) is a demanding task for companies. Due to the dynamic innovation cycles with new emerging technologies, many IT innovation investment decisions follow a bandwagon behavior or fixed investment strategies. Instead of optimizing the IT innovation budget's allocation to mature or fashionable IT innovations and following a mindful investment strategy, fixed strategies with naïve diversification are the rule in practice. To contribute to the decision making process regarding the IT innovation budget's allocation, we aim on the optimized allocation to mature and fashionable IT innovations via a dynamic optimization model incorporating the idiosyncrasies of IT innovations and a company's innovator profile. Though determining the optimum in practice seems to be virtually impossible, we argue that deviating above or below the theoretical optimum leads to a substantial difference regarding the IT innovation budget's value contribution. For that we examine the valuation error resulting from under- or overinvesting in mature and fashionable IT innovations due to deviating from the theoretical optimum. By providing our ex ante dynamic optimization model and analysis we contribute to the decision making process regarding the engagement in new emerging IT innovations.

Keywords: IT innovation investments, IT fashions, decision making, budget allocation, IT strategy

1 Introduction

The dynamic development of information technology (IT) regularly forces companies to decide whether, when and to which extent to adopt new emerging IT innovations or not (Swanson and Ramiller, 2004). Whereas IT innovations for many companies play a crucial role to create and sustain competitive advantage (Stratopoulos and Jee-Hae, 2010), rash investments in failing technologies like during the dot-com bubble which lead to a wave of bankrupts are the best warning not to engage with IT innovations which undergo a transient hype phase without thorough considerations (Fenn and Raskino, 2008). In contrast to *mature* IT innovations which already have been widely accepted and institutionalized, such IT innovations within a hyped phase due to their peculiarities are defined as *fashionable* IT innovations e.g. by Wang (2010), Baskerville and Myers (2009), as well as Fichman (2004a). Hence, IT fashion research examines a phase before a technology has to cross the chasm from being a fashionable IT innovation into a mature IT innovation (Wang 2010) and bears both, the potential to develop into a disruptive as well as into a losing technology. Due to their novelty, fashionable IT innovations often heavily affect the IT infrastructure, business processes, or even the whole business model making investing in a losing technology a major threat (Fenn and Raskino, 2008). To learn about the chances and limitations of new technologies, companies "[…] need a steady stream of IT experiments […]" (Ross and Beath, 2002) and consider fashionable IT innovations not merely as a dayfly but as a persistent share of its innovation strategy (Stratopoulos and Jee-Hae, 2010). This raises our first research question:

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

Though in theory there might exist an optimal allocation ratio regarding mature and fashionable IT innovations, management's uncertainty, missing data or political reasons often lead to fixed rules within IT innovation investment strategies (Nagji and Tuff, 2012; Swanson and Ramiller, 2004). 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 mostly deviate from the theoretical optimum and thus result in the error of under- or overinvestments. This raises our second research question.

RQ2. How substantial is the potential error of under- vs. overinvesting in fashionable IT innovations resulting from common fixed strategies widely applied in practice?

As our literature review will show, research that considers fashionable IT innovations in a formal-deductive and mathematical model to the best of our knowledge is virtually absent. Williams et al. (2009) even demand for more variety regarding the methodology in IT adoption and diffusion research to avoid overall homogeneity. To contribute to the closure of this research gap, we apply a design-science driven research, a well-recognized methodology that aims on creating and applying specific artifacts to gain knowledge of a problem domain and so solves organizational problems (Hevner et al., 2004; Peffers et al., 2008; Wacker, 1998). This approach is furthermore closely related to the basic idea of the research cycle of Meredith et al. (1989) who emphasize that for research areas that are not thoroughly examined yet, qualitatively and mathematically approaches that predict first results provide the basis for generating hypothesis for future tests within empirical research. By that, we transfer central findings of IT innovation and IT fashion theory into a dynamic optimization model that enables determining the optimal IT innovation strategy considering mature and fashionable IT innovations. Knowing the optimal investment strategy then allows us to analyze the potential error of under- and overinvestments in mature or fashionable IT innovations that results from fixed investment strategies based on gut feeling decisions. The paper is organized as follows: First, we describe the idiosyncrasies of engagements with fashionable IT innovations more in detail and give an overview on relevant literature. After that, we develop and analyze the model which aims on providing i) a new methodological approach in IT innovation research regarding fashionable IT innovations and ii) further assistance to practioner's decisions. In the last section we discuss limitations and future research potential.

2 Problem Context and Related Work

In the next paragraph, we take a look at the lifecycle, an IT innovation experiences from being an experiment towards a broadly institutionalized technology and so depict the peculiarities in decision making regarding IT innovations within different stages of maturity. Subsequently, we review relevant literature regarding IT innovations and focus on literature which aims on the idiosyncrasies of fashionable IT innovations that require certain decision making approaches.

2.1 IT innovation lifecycle

Whereas traditional IT innovation research focuses on a lifecycle phase in which an IT innovation has already been widely accepted and taken for granted (=mature IT innovation), IT fashion research concentrates on IT innovations within their very early and middle phase of diffusion in which the "[…] legitimacy stems from fashion, regardless of what the destiny of the innovation eventually turns out to be." (Wang, 2010) (=fashionable IT innovation). The discourse around IT innovations and their adoption often is accompanied by fashion waves (Abrahamson and Fairchild, 1999) which follow a lifecycle that is closely linked to the concept of technology adoption cycles, originally sketched by Rogers (2003), and extended into "Hype Cycles" by Gartner Inc. (Fenn and Raskino, 2008) from a practitioner's view. This concept illustrates an IT innovation's lifecycle starting with a *technology trigger* and excessive publicity leading to over-enthusiasm and investment decisions on the basis of bandwagon behavior. The hype usually ends up in a peak of *inflated expectations* before the hype fades away in a *trough of disillusionment*. These three milestones mark the phase in which an IT innovation has fashionable aspects and an unclear destiny. After this phase, opportunistic adopters often enough abandon ship, IT projects are scaled back and fashionable IT innovations might get stranded. Only few technologies are worth to continue experimenting with and to put solid hard work in understanding the technology's applicability, its risks and its benefits leading to a *slope of enlightenment* for the technology followed by a *plateau of productivity* (Fenn and Raskino, 2008). Hence, next to the technological risk that is associated with nearly every type of IT investment, investments in fashionable IT innovations additionally are associated with the risk of investing in a losing technology that never becomes institutionalized. In what follows, we show that common IT innovation literature tends to neglect these idiosyncrasies and why IT fashion research is a valuable contribution to (IT) innovation literature, especially regarding the lack of quantitative decision models.

2.2 Review of relevant literature

Traditional IT innovation literature mainly focuses on a set of variables like company size, structure, knowledge, or compatibility which form the company's 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, 2004b). However, several authors claim to consider other IT innovation related issues (e.g. probability of institutionalization) in the evaluation of IT innovation investments (Fichman, 2004a). 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 innovation strategy and apply a well-founded decision process. Such a decision process thereby e.g. should consider the expected destiny, i.e. that some IT innovations reach institutionalization whereas some are completely abandoned, adequately. In contrast, IT fashion theory extends the traditional focus on e.g., company size, structure, knowledge, and 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). For the justification of separate IT fashion research, Fichman (2004b) offers arguments that distinguish management fashions from IT fashions even though in practice, fashionable IT innovations often have administrative components and vice versa. They state that in contrast to management fashions, IT fashions often come along with high switching costs e.g. through the restructuring of IT infrastructure, tangible artifacts like software and hardware and are characterized by uniqueness due to various company individual implementation details which imply a different kind of decision-making processes (Wang, 2010). Lee and Collar (2003) found that IT fashions come more quickly 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. In this context, Dos Santos and Pfeffers (1995) demonstrated that the very early engagement in new IT can add over proportional value. Hoppe (2000) in a game theory approach 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 were investing in fashionable IT innovations have better reputation and improved performance due to over proportional returns resulting from competitive advantages in the long term. In the context of innovation persistence, Stratopoulos and Jee-Hae (2010) found that for becoming a systematic innovator, steady engagements in new emerging IT innovations are required and that systematic innovators are more likely to outperform their competitors in the long-run. Though all this research provides valuable insights into the advantageousness of engagement in fashionable IT innovations and so contributes to decisions in this context, it stays on a rather generic level and does not provide decision models that consider the idiosyncrasies of fashionable IT innovations. However, the consideration of e.g., 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, 2004b). As one of the few, Kauffman and Li (2005) address this challenge and by applying a real options approach argue that technology adopters are better off by deferring investments until the technology's probability to become widely accepted reaches a critical threshold of ~60%. In contrast, most research even indicates a "more innovation is better" advice without differentiation in the allocation of a strategic IT innovation budget to different types of IT innovations. However, as determining this point of time equals a herculean task, the question of thoroughly analysing whether, when and to which extent to invest in fashionable IT innovations remains unanswered. Hence, there is a rather high research need with respect to the ex ante analysis of investments in fashionable IT innovations as part of an IT innovation strategy. Thus, our model's scope is the ex ante decision support for the allocation of a strategic IT innovation budget by firmly considering mature and fashionable IT innovations as investment alternatives. In a second step, we analyse the potential error that steams from applying fixed investment strategies as emphasized by e.g., Ross and Beath (2002) and Nagij and Tuff (2012) as such strategies might lead to under- or overinvestments in mature or fashionable IT innovations compared to the theoretical optimum. Our aim is to examine whether a strategy that under- or overinvests in mature and fashionable IT innovations is better off in case the theoretical optimum cannot be calculated exactly in practice.

3 Towards an optimal IT innovation investment strategy

3.1 The Model

In accordance with the design-science research guidelines by Hevner et al. (2004) we in the following develop our artifact, a dynamic optimization model for determining the optimal allocation of a strategic IT innovation budget to mature and 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). For that, we describe a scenario in which a company decides on how to allocate an initial strategic (i.e. not periodic but mid-term oriented) IT innovation budget (ITIB) to two different types of IT innovations (mature IT innovations vs. fashionable IT innovations) in the next two periods to maximize its expected cash flows. 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. Engagements promise first mover and therefore competitive 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).

The part of the strategic IT innovation budget that is not allocated to mature or fashionable IT innovations in $t = 0$ is hold back as a strategic reserve to increase the investment budget later. It is used when the company intends to defer an investment until more information about an IT innovation's development is available. The resulting cash flows again are allocated in the same manner in $t = 1$ to generate cash flows in $t = 2$. Therefore, our model aims on determining the optimal allocation of the company's initial ITIB in $t = 0$ and the optimal allocation of the resulting cash flows in $t = 1$ to maximize the cash flows in $t = 2$ within a dynamic optimization model. Incorporating two periods in our analysis thereby allows us to model the most relevant time periods regarding the idiosyncrasies of fashionable IT innovations. Additionally, it keeps the mathematical model as simple as possible by simultaneously not limiting the central propositions for research and practice. In the following section we will outline the central assumptions of our model.

3.2 Assumptions and Objective Function

Assumption 1: *In $t = 0$ we assume an initial strategic IT innovation budget $ITIB_0 > 0$ that is provided from the central IT budgeting planning to the IT innovation portfolio as strategic budget to work with for the planning horizon. Within the planning horizon, no extra budget will be provided 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 $t = 0,1$. Furthermore, we define $1 - a_t^N - a_t^F \geq 0$ as the share of $ITIB_t$ to be hold back in a strategic investment reserve R that allows deferring the investments until more information is available* (Hoppe 2000; Lu and Ramamurthy 2010).

Figure 1 shows the split of $ITIB_0$ into the two investment alternatives F, N, R and the cash flows that are realized in $t = 1$ (=$ITIB_1$) which then are allocated and generate cash flows in $t = 2$.

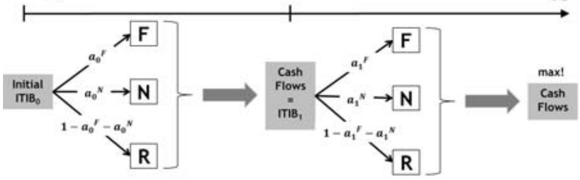

Figure 1. The decision setting in t=0,1,2

Assumption 2: *The IT innovation portfolio's cash flow CF_t^{PF} for $t = 1,2$ consists of the investment's cash flows CF_t^F that result from the fashionable IT innovation investment, the cash flows CF_t^N that* *result from the mature IT innovation investment and the cash flows CF_t^R that result from liquidating the strategic reserve and its interest payments (e.g. resulting from investments in risk free assets).*

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

To model the idiosyncrasies of the decision setting in more detail, we in the following take a closer look at the cash flows that are realized by N and F as well as 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 that was allocated to F, N, and R in the previous period. For simplification and easier interpretation, the cash flows in $t = 2$ are assumed to be a perpetuity and can be interpreted as the cash flows that are realized by the IT innovation budget from $t = 2$ on* (Copeland et al., 2005). *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 depending on a_{t-1}^i with $i \in [N, F]$ and $t = 1{,}2$:*

$$CF_t^i(a_{t-1}^i) = \left(a_{t-1}^i * ITIB_{t-1}\right)^{q_s^i} * v \text{ with } q_s^i \in [0,1),\ i \in \{N, F\},\ t \in \{1,2\},\ s \in \{u, d\},\ v \in R^+$$

The assumption of a strictly monotonically increasing function is reasonable due to the fact that in general, a higher investment and therefore commitment into an IT innovation allows for a deeper engagement and understanding of the technology, broader implementation and therefore, more opportunities to create value out of the investment (Fichman, 2004b; Kimberly, 1981; Melville et al., 2004) later on. However, a pure "more is better" approach must not hold true for every IT innovation investment: As companies need a minimum engagement to enter a market or become familiar with a technology reasonably, a first engagement in IT innovation usually creates more value than the additional increase of an already quite high investment spending. We thus can argue that an increasing investment into 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). As an engagement in a failing fashionable IT innovation also can lead to zero cash flows, we in addition to the general cash flow form also model this important case.

The factor q_s^i with $i \in \{N, F\}$ and $s \in \{u, d\}$ that is constant over time can be interpreted as a technology specific impact factor that describes the impact degree of N and F, i.e. its general acceptance by customers or employees, 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 get 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_s^F with $s \in \{u, d\}$ generally to be higher than N's q_s^N with $s \in \{u, d\}$, i.e. $q_s^F > q_s^N \forall\, t = 1{,}2 \text{ with } s \in \{u, d\}$. 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 factor, i.e. $q_u^i > q_d^i \forall\, t = 1{,}2$ with $i \in \{N, F\}$ and by that incorporate uncertainty about the IT innovation's possible outcome (Fenn and Raskino, 2008). Whereas upside scenarios regarding an IT innovation can be interpreted as e.g., 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 can be characterized e.g., by difficulties within the integration in existing processes or even the case of getting stranded (in the case of fashionable IT innovations). 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 constant factor $v \in R^+$ can be interpreted as the company's individual innovator profile indicator describing its ability to engage economically, quickly and efficiently with an IT innovation (Fichman, 2004b; Swanson and Ramiller, 2004). As companies that innovate steadily have more experience in integrating new IT in an existing infrastructure, to make employees adopt the new technology and based on an IT innovation create products that get accepted by customers, we assume those companies to have a higher innovation profile indicator (Stratopoulos and Jee-Hae 2010). To enable an easier interpretation of the innovation profile v, we level a company that is on average or opportunistic innovative with $v^* \epsilon R^+$, non-innovators with $v < v^*$ and innovators, i.e. first and progressive movers with $v > v^*$ to transfer empirical findings by Stratopoulos and Jee-Hae (2010) as well as Lu and Ramamurthy (2010) into an analytical model.

Summarizing, both factors, the technology specific impact factor q_s^i with $i \epsilon \{N, F\}$ and $s \epsilon \{u, d\}$ as well as the company's individual innovator profile indicator $v \epsilon R^+$ 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: *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 future development within this very early phase of the adoption lifecycle can 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 at all in $t = 1$ and creates desirable cash flows in $t = 2$ (F^u with q_u^F). With $1 - p^i$ with $i \epsilon \{N, F\}$ we describe the probability that an investment in N creates below-average cash flows (N^d with q_d^N) in $t = 1{,}2$ or, in case of F, becomes a losing technology in $t = 1$ or creates below-average cash flows in $t = 2$ after institutionalization in $t = 1$. In case F gets stranded in $t = 1$ (leading to zero cash flows), the company in this case only depends on the cash flows resulting from N in $t = 1{,}2$.

Assumption 5: *The company is a risk neutral decision maker that aims on 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 $r > 0$ that is assumed to be constant for each period.*

Assuming a risk neutral decision maker for a company's IT innovation portfolio's decisions is reasonable as an IT innovation portfolio per definition deals with more risky investments than e.g. an IT asset portfolio that deals with infrastructure, operational data and routine processes (Maizlish and Handler, 2005; Ross and Beath, 2002). Hence, an approach with a risk-averse decision maker would possibly lead to inadequate conservative investment decisions limiting the company's innovativeness.

Cash Flows in t: The IT innovation portfolio PF in t realizes cash flows from the investments in F, N, and R, respectively. According to the 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 1 Scenarios for the IT innovation's cash flow

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

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

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 $t = 0$ ($ITIB_0$) forms the basis for further investments (=$ITIB_1$) in $t = 1$:

$$ITIB_1 = CF_1^F(a_0^F) + CF_1^N(a_0^N) + CF_1^R(a_0^F, a_0^N)$$

After describing the particular decision making problem and possible scenarios and cash flow outcomes for $t = 1,2$, we can now state the objective function of our model. According to the outlined decision problem, the company aims to maximize the net present value (NPV) of the IT innovation portfolio's expected cash flows $\mathrm{E}(\mathrm{CF}_t^{\mathrm{PF}})$ with $\mathrm{t} = 1,2$ by allocating $ITIB_0$ and $ITIB_1$to F, N, and R. Hence, the objective function is from the following form:

$$\max_{a_0^F, a_0^N, a_1^F, a_1^N} -ITIB_0 + \frac{E(CF_1^{PF})}{1+r} + \frac{E(CF_2^{PF})}{r*(1+r)} \quad s.t.$$
$$0 \leq a_t^i \leq 1 \qquad \forall t = 0,1;\ \forall\, i \in \{N, F\}$$
$$0 \leq a_t^F + a_t^N \leq 1 \qquad \forall t = 0,1$$
$$ITIB_t = CF_t^{PF}(a_{t-1}^F, a_{t-1}^N) \text{ with } t = 1$$

3.3 Model Evaluation

We approach this dynamic optimization problem by analyzing different scenarios regarding the evolution of F an N and conduct a roll-back analysis (Clemons and Weber, 1990). After that, the company repeats the optimization and possibly re-allocates its IT innovation strategy according to the realized scenarios or when new information is available. A real option approach as applied by Kauffman and Li (2005) or Fichman (2004a) might also have been suitable to address this decision setting but inherits restrictive assumptions as e.g., 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 can be realized by incorporating the results from the model in decisions regarding the allocation of a strategic IT innovation budget. According to Hevner et al. (2004), the analytical evaluation or gathering data by simulation are legitimate means for evaluating artifacts based on mathematical models. Thus, to derive first results, we conducted a Monte Carlo simulation, for which we generated 1,000 different investment settings in which we randomly changed *all* parameters of major influence. We chose 1,000 investment settings as the results changed only slightly with an increasing number of investment settings but on the other hand increased the simulation runtime rapidly. Table 2 shows the initial values and their ranges which are relevant for the simulation. For our analysis, the values in the table serve as starting points. For the sake of simplicity we in the following speak of v, q_s^i and p^i with $i \,\epsilon\, \{F, N\}$ and $s \,\epsilon\, \{u, d\}$ and assumed equal distributions as other distributions like Gaussian would not distort the general results but increase complexity. For the risk free interest rate r, we took an value $r = 0.1$ analog to Kauffman and Li (2005). We started our analysis and optimization with rather conservative values and let the relevant parameters range in conservative intervals to avoid distortion due to overoptimistic value estimations. Due to space restrictions, we in the following focus on the ex ante analysis in $t = 0$. Additionally, we analyse the potential error that occurs from deviating from the theoretical optimum by applying a fixed investment strategy. Thus, we are able to examine wheather under- or overinvestments in IT innovations are beneficial.

Parameter	Initial Value	Range
Company's individual innovator profile indicator v	100 (= v*)	70 – 130
Fashionable IT innovations impact factor q_u^F (upside scenario)	0.5	0.2 – 0.5
Fashionable IT innovations impact factor q_d^F (downside scenario)	0.3	0.05 – 0.3
Mature IT innovations impact factor q_u^N (upside scenario)	0.35	0.1 – 0.35
Mature IT innovations impact factor q_d^N (downside scenario)	0.2	0.01 – 0.2
Probability that fashionable IT innovation creates desirable cash flows p^F	0.05	0.01 – 0.2
Probability that mature IT innovation creates desirable cash flows p^N	0.4	0.2 – 0.4

Table 2 Data for Sensitivity Analysis and Monte Carlo Simulation

3.4 Simulation analysis

3.4.1 Simulation of all parameters

Simulating all parameters leads to a broad range of values for $a_0^{F^*}$ between 0.24% to 87.08%. This is due to the high number of possible constellations regarding the parameters. Analysing an extremly unrealistic case with e.g. a low value for p^F (4.45%), an average value for p^N (28.27%) which always is above 20% and simultaneously the unrealistic case of $q_u^F < q_u^N$ (which by our assumptions is even excluded) as well as the case of a below-average innovative company ($v = 71$) shows interesting and counter intuitive results. Even in this case, the company is better off by investing a very slight amount (1.25%) in fashionable IT innovations (see Figure 2). In this analysis, companies on average should invest a reasonable amount of about 16.36% in fashionable IT innovations.

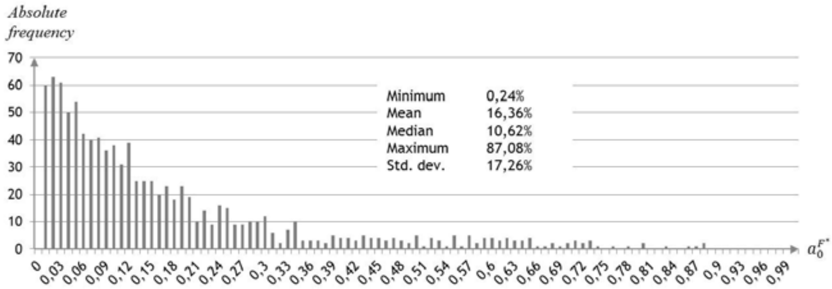

Figure 2. Results for $a_0^{F^*}$ after Monte Carlo Simulation regarding $q_u^F, q_d^F, q_u^N, q_d^N, p^F, p^N, v$

3.4.2 The error of fixed IT innovation investment strategies on a gut feeling

Though our results shows the existence of an optimal ex ante IT innovation portfolio investment strategy formally, 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 rules for IT innovation investment strategies. Previous literature empirically (Nagji and Tuff, 2012; Ross and Beath, 2002) provided such fixed investment rules for different kinds of (IT) innovations for different industries. 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. Taking our model, for each simulation run i with $i \in \{1, \dots, 1000\}$ we can determine the valuation error Δ_i^{err} by comparing the IT innovation portfolio's optimal NPV_i^{opt} with the $\text{NPV}_{i,j}^{fix}$ that results from applying a certain fixed investment strategy j (i.e., j represents one fixed combination of investment shares a_t^F and a_t^N):

$$\Delta_{i,j}^{err} = \frac{\text{NPV}_i^{opt} - \text{NPV}_{i,j}^{fix}}{\text{NPV}_i^{opt}}$$

To demonstrate the calculus, we regard different scenarios with fixed investment strategies regarding mature and fashionable IT innovation investments. To examine the valuation error, we keep one share constant (with $a_t^N = 0.2$ and $a_t^F = 0.1$, respectively with $t = 0{,}1$) and slightly change the other one (with $a_t^F \in [0; 0.2]$ and $a_t^N \in [0; 0.4]$ with $t = 0{,}1$, respectively) and so obtain different fixed strategies j. For every fixed strategy j, we calculate the *average valuation error* $\Delta_{avg,j}^{err}$:

$$\Delta_{avg,j}^{err} = \frac{1}{1000} \cdot \sum_{i=1}^{1000} \Delta_{i,j}^{err}$$

In the following, we illustrate the $\Delta_{avg,j}^{err}$ depending on the share that is allocated to fashionable IT Innovations (Figure 3) and mature IT innovations, respectively (Figure 4).

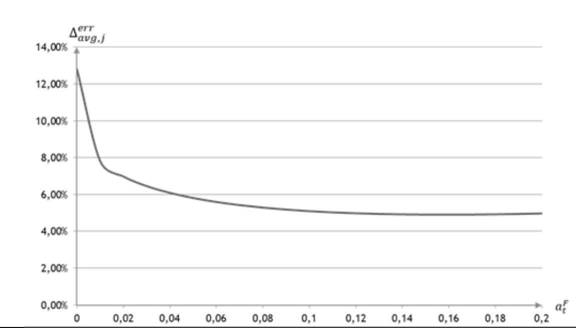

Figure 3. $\Delta_{avg,j}^{err}$ *depending on* a_t^F

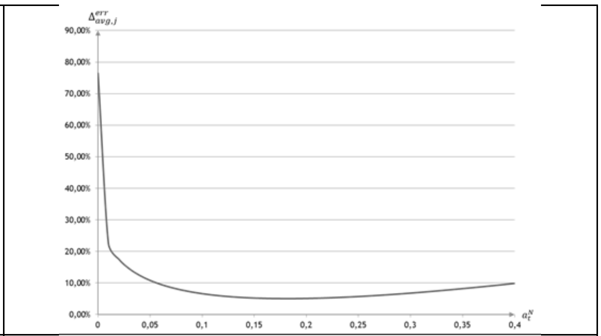

Figure 4. $\Delta_{avg,j}^{err}$ *depending on* a_t^N

Figure 3 and Figure 4 illustrate that the average valuation error of fixed investment strategies ranges between 4.90% and 12.80% when deviating from the optimum regarding fashionable IT innovations (with an average $a_t^{F*} = 16.36\%$) and ranges between 5.04% and 76.45% when deviating from the optimum regarding mature IT innovations (with an average $a_t^{N*} = 18\%$). Hence, the potential damage is substantially higher when deviating from the optimum in mature IT innovations than in fashionable IT innovations. This is reasonable as an IT innovation portfolio requires basic and evolutionary IT innovations to ensure competitive advantage (Maizlish and Handler, 2005; Ross and Beath, 2002). Neglecting these important basic IT innovations and e.g. "gambling" with fashionable IT innovations or holding back too much in a strategic reserve destroys value. Furthermore, our results generally reveal that underinvesting (with respect to the theoretical optimum) generally leads to a profoundly higher marginal increase of the average valuation error than overinvesting.

3.4.3 Discussion of the results

Though different model settings, simplifying assumptions or model-specific parameters limit comparison between different research approaches, it is worth to discuss our results with regard to existing research: By applying our ex ante mathematical model and optimizing a strategic IT innovation budget allocation, we find an average optimal allocation to fashionable IT innovations of 16.36%. Thus, according to our model it is beneficial to invest a significant amount of the strategic IT innovation budget to technologies with a rather uncertain future development. We also find overinvestments in fashionable IT innovations as favorable compared to underinvestments and underinvestments in mature IT innovations to be a substantial threat. The results of our ex ante model basically are in line with previous qualitative and empirical findings like Nagji and Tuff (2012) who find that the most innovative companies in the technological sector on average invest about 15% of their innovation portfolio spendings in innovations that aim on breakthrough technologies. We also support the empirical findings of Ross and Beath (2002) who analyzed allocation of IT budgets to IT experiments in different industries and found ranges from 3% to 15% - values. The advantageousness of an early adopter strategy with significant engagements in fashionable IT innovations is comparable with the results of empirical research of Wang (2010), Lu and Ramamurthy (2010) or Dos Santos and Pfeffers (1995) who show that engagements in fashionable IT innovations and being a proactive IT leader leads to higher performance. The result of being better off by over-investing in fashionable IT innovations goes in line with Stratopoulos and Jee-Hae (2010) who emphasize the importance of persistent consideration of emerging IT innovations. We deviate from the findings of Kauffman and Li (2005) who suggest to adopt a new technology only when its probability to win is greater than 60% as we propose an investment strategy that tendentially leads to overinvestments in fashionable IT innovations to be beneficial even in case when the probability is considerably lower. In the following, we discuss practical implications, limitations of our approach as well as aspects worth to examine in future research.

4 Theoretical and practical implications and limitations

IT innovation investment decisions often enough follow a gut feeling rather than a well-founded analysis. We approach this challenge by a dynamic optimization model that optimizes the allocation of a strategic IT innovation budget to *mature and fashionable IT innovations.* We theoretically show the existence of an optimal investment strategy in fashionable and mature IT innovations which complies with the constraints of our decision framework. Our approach covers specifics of IT innovations like their uncertainty and their technology specific impact factor as well as company characteristics like the company's individual innovator profile. As determining such an optimal investment strategy in practice is limited due to missing parameter estimations, companies often apply fixed allocations to different IT innovations types. We address this challenge and analyse the average estimation error of different fixed IT innovation portfolio strategies that occurs by deviating from the optimal strategy. This allows for deriving the following implications for research and practice:

When randomly simulating all major influencing parameters, companies on average should invest a reasonable amount of their IT innovation budget in fashionable IT innovations even though their success probability has not reached a high threshold [*whether?*]

When applying a fixed strategy, a company is better of by an over-investment strategy regarding fashionable IT innovations than by an under-investing strategy [*when?*]

An IT innovation portfolio investment strategy that underinvests in mature IT innovations and instead e.g. "gambles" with fashionable IT innovations or holds back too much in a strategic reserve in the long-term destroys value [*to which extent?*]

Though we aim on a methodically rigor model that delivers initially reasonable results, it might not be applicable in practice without some adjustments. Following Kauffman and Xiaotong (2005), we aim on "[…] an analogy between the technical details of the decision model and the exigencies of its application in an appropriate managerial context". Despite the fact that our model pictures reality in a slightly constrained way, the results are comparable with previous qualitative and empirical literature and thus complements it by providing a basis for the ex ante decision support and improvement of an IT innovation investment strategy. The specific design of our ex ante decision situation, other guidelines and assumptions also might explain differences in results which partially deviate from previous research. Some aspects that are not covered or that need further methodological effort are the incorporation of switching costs, spill-over effects, risk, n-period analysis or learning aspects. Furthermore, an empirical testing of the model and its parameters as different dimensions of q or v with real world data is due to further research. Also, opposing our approach with different model settings of previous work and so analyzing differences or similarities of the results is not covered yet. It is also to mention that the model's inherent interpretation of the IT innovation's value is rather abstract, i.e. it is limited to deal with quantifiable and attributable value components. We also do not consider that a technology might require a minimum engagement. To sum it up, our model can serve as a basis for developing hypothesis which might be tested in further empirical research to close the research cycle between design-science and behavioral-science (Hevner et al., 2004; Wacker, 1998).

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