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NEVER CHANGE A RUNNING SYSTEM? HOW STATUS QUO-THINKING CAN INHIBIT SOFTWARE AS A SERVICE ADOPTION IN ORGANIZATIONS

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Abstract

Despite the "buzz" about Software as a Service (SaaS), decision makers still often refrain from replacing their existing in-house technologies with innovative IT services. Industry reports indicate that the skeptical attitude of decision makers stems primarily from a high degree of uncertainty that exists, for example, due to insufficient experience with the new technology, a lack of best practice approaches, and missing lighthouse projects. Whereas previous research is predominantly focused on the advantages of SaaS, behavioral economics conclusively demonstrate that reference points like the evaluation of the incumbent technology or a familiar product are oftentimes prevalent when decisions are made under uncertainty. In this context, Status Quo-Thinking may inhibit decisions in favor of potentially advantageous IT service innovations. Drawing on Prospect Theory and Status Quo Bias research, we derive and empirically test a research model that explicates the influence of the incumbent technology on the evaluation of SaaS. Based on a large-scale empirical study, we demonstrate that the decision makers' attitude toward SaaS is highly dependent on their current systems and their level of SaaS. A lack of SaaS experience will increase the impact of the Status Quo, thus inhibiting a potential advantageous adoption of the new technology.

Keywords: Status Quo Bias, Prospect Theory, Software as a Service (SaaS), Adoption.

1 Introduction

The World Economic Forum stated already in 2010 that "in addition to reducing operational costs, cloud technologies have become the basis for radical business innovation and new business models, and for significant improvements in the effectiveness of anyone using information technology" (World Economic Forum, 2010, p. 1). Fittingly, recent analyses of research institutes forecast the public cloud services market to reach a total of $204 billion in 2016 (e.g., Gartner, 2016; IDC, 2016; Synergy, 2016). A substantial part of that growth is contributed to Software as a Service (SaaS) – the provisioning of applications running on a cloud infrastructure – that will remain the dominant public cloud computing type at an estimated 20.3 percent growth rate resulting in forecasted revenues of roughly $37.7 billion in 2016 (e.g., Cisco, 2016; Gartner, 2016; IDC, 2016). Associated with a large variety of benefits like scalability, mobility or cost savings that are increasingly affirmed by practitioners, SaaS has been hailed as the future default software delivery solution (e.g., Dahlberg et al., 2017). Unsurprisingly, IDC predicts that the penetration of SaaS solutions compared to traditional software deployment will be over 25 percent by 2020 (IDC, 2014). However, especially current European reports show that nearly 80 percent of EU enterprises still do not use cloud services implying that adoption rates are not as high as expected (Eurostat, 2016). Given its role as state-of-the-art technology and innovative service model in an evolving business environment, it is thus crucial to understand why many decision makers today still refrain from using SaaS in a business environment shaped by increased mobility and disruptive marketing strategies (e.g., Lin and Chen, 2012).

Previous research explains the non-adoption of SaaS in organizations either with legal or strategic requirements to keep data processing completely in-house or as the result of a risk-benefit-analysis (e.g., Benlian and Hess, 2011). Whereas theoretical studies mostly consider purely rational decision makers, experts claim that decision makers “have been more protective of their existing infrastructure and, in many cases, have been the biggest obstacle to cloud-based solutions” (van der Meulen and Rivera, 2015). This non-rational behavior is a common assumption in behavioral economics studies when analyzing decisions that are made under uncertainty. Decision makers actually violate the axioms of rational choice under uncertainty due to cognitive biases or “shortcuts” that compensate for a lack of information or experience (Tversky and Kahneman, 1975). To account for these shortcuts, Kahneman and Tversky (1979) established the so-called Prospect Theory. This theory postulates that people faced with a decision under uncertainty will derive utility from gains and losses measured in relation to some reference points rather than on final assets. The dependence on reference points has been frequently discussed in individual strategic choice contexts and was demonstrated in several empirical studies on the assessment of new products and services (e.g., Bamberger and Fiegenbaum, 1996; Shoham and Fiegenbaum, 2002). Surprisingly, the SaaS technology adoption literature has largely overlooked this reference-dependence although the decision to adopt SaaS generally entails a high degree of uncertainty due to the unknown complexity of IT security risks, lack of previous experience with cloud-based technologies, or missing best practices and lighthouse projects in the industry (e.g., Eduserv, 2015; Eurostat, 2014; Lin and Chen, 2012). The decision to be protective of their existing (incumbent) infrastructure, i.e., the exaggerated preference for maintaining the current state of affairs, hints at another cognitive bias, namely the influence of Status Quo-Thinking (Samuelson and Zeckhauser, 1988). Status Quo Bias itself has been demonstrated in a wide range of studies of consumer and investment behavior and is increasingly used in management of information systems (MIS) research (Fleischmann et al., 2014). However, research on software selection and particularly studies investigating the intention to adopt cloud based services did not account for this cognitive bias in decision making.

To account for this research gap, we first investigated the influence of reference-dependence on SaaS adoption at the organizational level and from there, analyzed how this dependency is affected by Status Quo-Thinking (e.g., Gerlach et al., 2014; Schweitzer, 1995). The distinctiveness of the Status Quo Bias depends on the degree of uncertainty, i.e., the lack of information and experience decision-makers are faced with. Based on the data of a large scale empirical study with decision makers in charge of the organizational IT, we confirmed our assumptions in a two-step approach: In the first step, we demonstrate the strong influence of the assessment and prevalence of the incumbent in-house technology on decision makers’ attitudes toward a new technology – in our case SaaS. In our second step, we uncover the effect of the Status Quo Bias by comparing experienced and non-experienced or less-experienced decision makers. We specifically chose SaaS as a clearly definable object of investigation given that the majority of organizations will need to evaluate whether to adopt SaaS as a new technological service model now or in the near future due to the increasing amount of data processing and the demand for mobility (e.g., McLellan, 2016; Rivera and van der Meulen, 2014).

Our study provides several theoretical and practical implications. Given that virtually all technology adoptions nowadays imply a replacement decision, our study highlights the relevance of reference-dependence in MIS research. In this regard, it is essential for future IS research to acknowledge that Status Quo-Thinking has a profound effect on decision-making processes regarding new technology acceptance in organizations. Our findings are also highly relevant to both providers of SaaS and decision makers of (potential) customer organizations. Providers should consider the varying degrees of Status Quo-Thinking and group their customers according to their level of SaaS experience. These identified customer groups can be addressed appropriately and more effectively by adapting marketing and sales strategies accordingly, whereas decision makers need to acknowledge the role of reference points and Status Quo-Thinking to avoid missing out on beneficial technological developments. Joining expert roundtables or including objective assessors could reduce the influence of the Status Quo Bias in decision-making processes. These measures can reduce the possibility that Status Quo-Thinking inhibits SaaS adoption even if the new technology would objectively be the better option.

2 Theoretical Background and Hypothesis Development

2.1 Technology Adoption Models and Rational Choice

There is a rich tradition in technology acceptance and adoption research. The theories primarily used to study the acceptance and adoption of innovations in information systems or information technologies generally originate in social psychology, such as Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980) and its extension Theory of Planned Behavior (TPB) (Ajzen, 1985). Drawing on TRA, many researchers added constructs or derived new models such as Davis' (1986) Technology Acceptance Model (TAM) or Venkatesh et al. (2003) who later consolidated the aforementioned and five further models into the Unified Theory of Acceptance and Use of Technology (UTAUT).

Despite different factors and research model designs, the majority of studies base their assumptions on rational choice, i.e., the rational weighing up of costs and benefits concerning the technology adoption. Specifically, perceived risks and perceived benefits are often singled out and commonly considered as decisive antecedents of behavioral intention or attitude toward SaaS (e.g., Benlian and Hess, 2011) or sometimes described as drivers and inhibitors of SaaS adoption (e.g., Benlian et al., 2009; Lee and Chae, 2013). Several studies look at risks and benefits as relative advantage, i.e., already implicitly weighing up potential benefits of a new technology with the current advantages of the incumbent technology (e.g., Chau, 1996; Wu and Wang, 2005).

In line with the predominant literature stream, we draw on a benefit-risk framework in an organizational setting. Previous research oftentimes studied differences in the perceptions of IT executives' in both SaaS adopter and non-adopter firms, but they did not link the differences they found directly to cognitive biases (Benlian and Hess, 2011). Contrarily, consumer studies went further and highlighted the importance of reference points as an "anchor" for decisions to either replace or stick to the incumbent technology or product (e.g., Moqbel and Bartelt, 2015; Roster and Richins). This dependence on reference points often explains the influence of the incumbent technology when people have to analyze the relative advantage of a new technology during a decision-making process under uncertainty (e.g., Gerlach et al., 2014). Accordingly, it is important to consider Prospect Theory and Status Quo research in the context of organizational SaaS adoption.

2.2 Prospect Theory, Status Quo Bias, and Hypothesis Development

Prospect Theory was designed to analyze decision-making processes under uncertainty by considering so-called certainty and isolation effects (Kahneman and Tversky, 1979). These two effects assume that decisions do not necessarily follow mathematical optimality (i.e., the rational weighing up of risks and benefits and their probability weights) due to several reasons: people either underestimate hardly probable outcomes in comparison with certain outcomes and/or people base their decisions rather on change of wealth than on total wealth, i.e., an absolute outcome (Kahneman and Tversky, 1979). Accordingly, Prospect Theory postulates that decision makers' value functions are rather dependent on reference points than on the actual final outcome. These reference points are defined as the neutral position used by decision makers in order to determine the extent to which the expected outcomes of a decision constitute gains (i.e., above this position) or losses (i.e., below this position) (Kahneman and Tversky, 1979). Kahneman and Tversky (1984) argue that individuals set up mental accounts to specify advantages and disadvantages associated with the offered option(s) when faced with a transaction or trade decision relative to a certain reference point. Several studies used Prospect Theory to analyze strategic choice and risk/return tradeoffs in organizational decision making (e.g., Fiegenbaum et al., 1996; Shoham and Fiegenbaum, 2002; Sinha, 1994). It is argued, therefore, that managerial decision processes often depend on reference points because many decisions must be made without advanced knowledge of their full impact and are thereby made under uncertainty. A similar utilization of reference points is at times applied in replacement decisions regarding consumer goods (e.g., Gerlach et al., 2014; Roster and Richins, 2009).

Based on the theoretical underpinnings of Prospect Theory, it can be assumed that a replacement decision in the context of technology adoption generally entails a decision between opting for a new technology or maintaining the incumbent technology, i.e., the enterprise software that is currently hosted and operated in-house on the organization's IT infrastructure. An aggravating factor is the lack of historical data and experiences that inhibits a well-informed, more rational decision-making process. The absence of information or experience is pervasive in the context of service innovations as lighthouse projects and hard facts about the realization of assumed risks and benefits are missing. To overcome this issue, it can be assumed that the incumbent technology will serve as a reference point for the assessment of a new technology (e.g., Kahneman and Tversky, 1979; Shoham and Fiegenbaum, 2002). Consequently, decision makers will compare the new technology with the incumbent technology because experience and knowledge are available due to the familiarity in this regard. For example, when it comes to the decision whether to replace an existing in-house application with a new SaaS application, we assume that the attitudinal beliefs toward incumbent in-house technologies (i.e., attitudinal beliefs toward the currently used, well-known technology) will serve as reference points for the decision makers when forming the attitudinal beliefs toward new, yet partly unknown, SaaS technologies. As our research model is based on a risk-benefit framework frequently utilized by previous research in technology adoption (e.g., Benlian and Hess, 2011), the attitudinal beliefs are formed by the juxtaposition of perceived benefits and risks. Therefore, the decision makers perceived benefits of a new SaaS technology will be influenced by the perceived benefits of the incumbent in-house systems that serve as a reference point. Furthermore, decision makers with little knowledge and experience will tend to underestimate the perceived benefits of SaaS in comparison with their familiar incumbent system. If the level of perceived benefits of the incumbent system is high, replacing this system will be regarded as futile. Logically, decision makers who are fully satisfied with their current in-house system will not regard the potential benefits of a new SaaS solution as equally high. Simultaneously, a decision maker who perceives the in-house system, for example, as costly and unreliable, will be more prone to change and will not consider this deviation from a certain outcome (i.e., subsequent use of the incumbent system) as a loss. Accordingly, decision makers who perceive the risks of their incumbent system as high, are more likely to consider a new SaaS technology to be less risky. Therefore, we hypothesize:

H1a: Perceived benefits of in-house systems are negatively associated with the decision makers' perceived benefits of SaaS.

Analogously, we assume the same influence regarding the evaluation and reference-dependence of the perceived risks:

H1b: Perceived risks of in-house systems are negatively associated with the decision makers' perceived risks of SaaS.

The benefits and risks associated with a new technology are fundamental in technology adoption decisions. Thus, previous studies in SaaS adoption show that behavior and intentions are largely determined by weighing up risks and benefits (e.g., Benlian and Hess, 2011). These overall perceived risks and benefits include financial, strategic, security, performance, and management dimensions (Benlian and Hess, 2011). In line with previous SaaS research (e.g., Benlian and Hess, 2010; Benlian and Hess, 2011; Lee, 2009), we expect perceived risks to generally have a negative impact on decision makers' intentions to adopt a SaaS technology. For example, if decision makers perceive a high risk of downtime errors and data loss to be associated with SaaS technologies, they will be less likely to consider an adoption of this new SaaS technology. On the other hand, the perceived benefits are generally expected to positively influence decision makers' intentions to adopt. For example, if decision makers perceive SaaS technologies to be associated with potential cost reductions (e.g., due to lower server administration costs) their intention to adopt SaaS will be positively influenced. Therefore, high perceived benefits will more likely lead to an intention to adopt, whereas the perceived risks of SaaS will inhibit the intention to adopt. Accordingly, we further hypothesize:

H2a: Perceived benefits of SaaS are positively associated with the decision makers' intention to adopt SaaS.

H2b: Perceived risks of SaaS are negatively associated with the decision makers' intention to adopt SaaS.

Building on Prospect Theory and several experiments, Tversky and Kahneman (1985) discovered that decision makers prefer to be passive and inactive rather than experiencing negative results due to their actions or decisions. Some literature refers to this concept as reference point bias (Levy, 1997), whereas a more common stream of research coined the term Status Quo Bias as an effect of the loss aversion discussed in Prospect Theory (Kahneman et al., 1991; Samuelson and Zeckhauser, 1988). Loss aversion entails an overestimation of certain positive outcomes, whereas potential losses are weighted disproportionately. This demonstrates the preference for the current state of affairs, i.e., if individuals take the Status Quo as a reference point, then they will perceive any deviation from it as loss. Therefore, a decision maker will avoid change and an unknown outcome unless the advantages clearly outweigh the perceived disadvantages. Another explanation for the Status Quo Bias is provided by Zajonc (1968) and Bornstein (1989) who argue that mere exposure to a stimulus (i.e., the incumbent product) enhances the attitude toward it and, therefore, argue that familiarity leads to liking.

A well-known example for the maintenance of the Status Quo is the QWERTY keyboard. Although a different arrangement of letters could lead to a more productive and better keyboard, QWERTY is still omnipresent because switching from the Status Quo could entail huge costs of retraining individuals and replacing the current design in systems and devices (David, 1985). Especially, research on replacement decisions regarding (technological) consumer goods consider these high potential switching costs to inhibit a change from the Status Quo (e.g., Moqbel and Bartelt, 2015; Roster and Richins, 2009). Studies focusing on technology systems are increasingly building on these findings adding further contributing factors like habit or inertia (Kim and Kankanhalli, 2009; Polites and Karahanna, 2012). Almost all of these studies attribute the Status Quo Bias at least partially to insufficient available information and experience. Past experiences serve as an "anchor" or "frame" for decisions as decision makers frequently do not exclusively follow rational concepts of mathematical optimality (e.g., Schwenk, 1984; Slovic, 1975).

In line with previous research, we expect that decision makers in companies that already possess a certain degree of knowledge and past experience will demonstrate a lower Status Quo Bias in comparison to less or non-experienced decision makers. Decision makers with a low level of SaaS experience, will be more affected by the Status Quo Bias because they overestimate the losses that they would encounter when replacing the incumbent technology. Therefore, the correlation postulated in hypotheses H1a and H1b will be increased. On the other hand, decision makers who already possess a SaaS solution among their incumbent in-house technology will draw on the experience that they already accumulated with SaaS. Therefore, their decision-making process will be better informed and consequently less affected by Status Quo-Thinking. Greater experience and further facts available to decision makers will enable a more "rational" decision making process (Bazerman, 2008). For example, experienced decision makers can judge the perceived benefits like cost reductions without drawing upon a comparison to their incumbent system because a previous adoption of a SaaS technology already proved to be cost-efficient. Similarly, experienced decision makers will evaluate the perceived risks of SaaS depending on past experience and be less affected by Status Quo Bias. Whereas, inexperienced decision makers might, for example, believe that downtime issues are more pronounced in contrast to their reliable in-house technology and will thus attribute higher perceived risks to a new SaaS technology. Hence, we hypothesize:

H3a: Perceived benefits of in-house systems will have a stronger negative association with the perceived benefits of SaaS for organizations with no or low SaaS experience than for organizations with SaaS experience.

H3b: Perceived risks of in-house systems will have a stronger negative association with the perceived risks of SaaS for organizations with no or low SaaS experience than for organizations with SaaS experience.

The research model is shown in Figure 1.

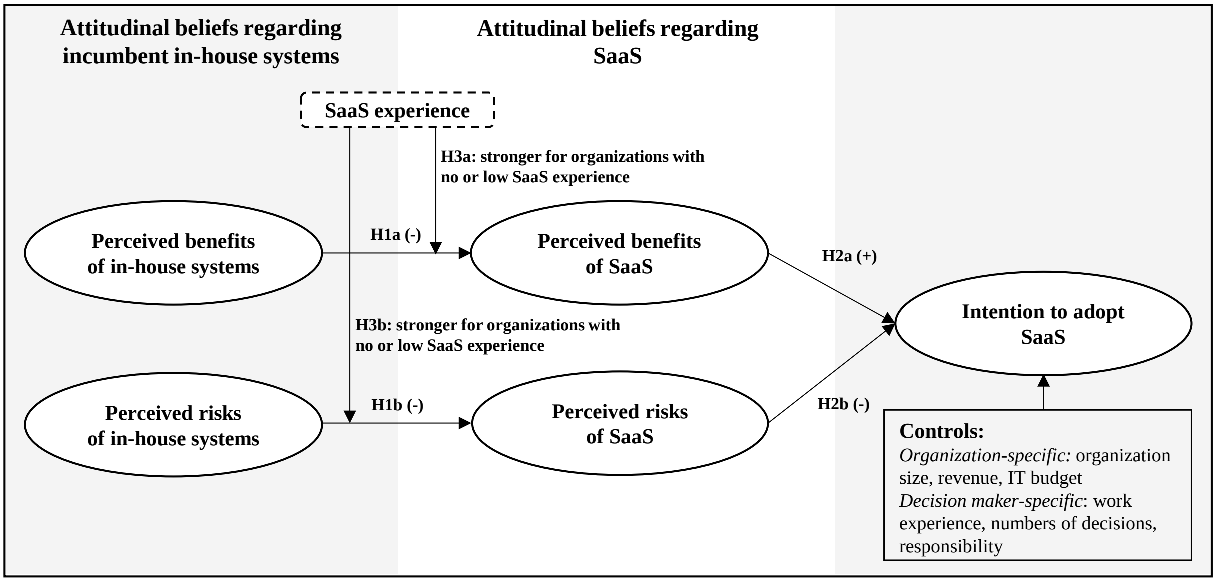

Figure 1. Research Model

3 Research Methodology and Data Analysis

3.1 Survey Administration and Sample Characteristics

Construct validity was established by adopting validated measurement items from previous research studies with minor changes in wording. All latent constructs were reflective and measured with multiple items on a 7-point Likert scale. To ensure a consistent understanding of enterprise software in case of in-house systems and in case of SaaS, we used the following definitions within the study:

- **Enterprise software** is defined as business applications, such as Customer Relationship Management (CRM) systems, Enterprise Resource Planning (ERP) systems, or Project Management (PM) applications.
- **SaaS** is defined as enterprise software provided by a supplier and accessible via a public network, such as the Internet (i.e., public cloud).
- **In-house systems** are defined as enterprise software that is hosted and operated on the organization's IT infrastructure.

As suggested by previous research, we included work experience (in years), numbers of sourcing decisions already made, the responsibility for sourcing decisions in the organization (1=not responsible at all - 4=completely responsible), organization size (revenue and number of employees), and IT budget as controls in our research model (Benlian, 2009; Hsu et al., 2015). We pre-validated our measurement model in a pretest with 8 MIS researchers by using a cognitive interview technique. The pretest resulted in minor changes to improve the clarity of the model. Our study's final measurement items are shown in Table 1.

Constructs	Items	Source
Perceived risks	How do you evaluate the overall risk (i.e., financial, strategic, security, performance, and management risks) associated with adoption of [in-house / SaaS] applications? (1=not risky at all - 7=extremely risky)	Based on Featherman and Pavlou (2003)
	How do you evaluate the risk that the expected benefits of adopting [in-house / SaaS] applications will not materialize? (1=not risky at all - 7=extremely risky)	
	How do you evaluate the danger that is generally associated with the adoption of [in-house / SaaS] applications? (1=not risky at all - 7=extremely risky)	
Perceived benefits	The overall advantage of adopting [In House / SaaS] applications is… (1=very low - 7=extremely high)	Based on Gewald and Dibbern (2009)
	The potential cost reduction associated with the adoption of [in-house / SaaS] applications is... (1=very low - 7=extremely high)	
	Overall, I consider [in-house / SaaS] adoption to be a useful strategic option. (1=strongly disagree - 7=strongly agree)	
Intention	If there is a superior offer, a SaaS solution should be used for the application domain that I am in charge of. (1=strongly disagree - 7=strongly agree)	Based on Gewald and Dibbern (2009)
	Our company should increase the existing level of adopting SaaS applications. (1=strongly disagree - 7=strongly agree)	
	I support the further adoption of SaaS applications for the application domain that I am in charge of. (1=strongly disagree - 7=strongly agree)	

Table 1. Overview of Constructs

Our quantitative study was conducted between March 17 and May 1, 2016 in a European country. In a key informant approach, we contacted a total of 1,126 decision makers from organizations of various industries via a contact request on an online social business network. To encourage participation, a management report about the results was offered to the participants. A total of 251 (22.3%) of the 1,126 contacted decision makers agreed to participate in our study and were sent links to access the online survey. One week after sending the invitation, a reminder was sent via another direct message on the social business network. With 131 completed surveys, the response rate was 11.6%. Two main reasons were given for not participating: the contacted decision makers either stated time pressure or that their organizations do not participate in such studies in general. Altogether, 4 of the 131 participants stated to be not responsible for sourcing decisions in their organizations and 4 data sets were identified to have poor data quality. These 8 data sets were excluded from the data analysis, which is therefore based on 123 valid data sets. The sample characteristics can be extracted from the following Table 2.

Company size (number of employees)		**Position**	
Small (<50)	36 (29.3%)	CEO	3 (2.4%)
Medium (50-249)	18 (14.6%)	CIO	73 (59.3%)
Corporation (>249)	69 (56.1%)	CTO	20 (16.3%)
Sales p.a.		IT Manager	21 (17.1%)
<1 m EUR	22 (17.9%)	Others	6 (4.9%)
1-9 m EUR	23 (18.7%)	**Work experience**	
10-99 m EUR	23 (18.7%)	1-5 years	16 (13.0%)
>99 m EUR	55 (44.7%)	6-10 years	30 (24.4%)
		11 years and more	77 (62.6%)

Table 2. Overview of Sample Characteristics

In addition to these sample characteristics, we further analyzed the differences within our sample according to the proportion of participating industry sectors and the respective average level of SaaS experience within those sectors. Table 3 shows the proportion of each industry sector relative to the overall sample and the average level of self-reported SaaS experience in each industry (0%=complete absence of SaaS use-100%=all enterprise applications deployed as a service). According to our analysis, most respondents work in IT, Professional Services, and Manufacturing and the highest experience levels are reported by decision makers in Telecommunications, IT, Retail, and Professional Services.

Industry sector	Proportion of total sample	Average SaaS experience
Real Estate	0.8%	0 %
Travel & Tourism	0.8%	0 %
Education & Administration	4.1%	1.20 %
Pharmacology & Medical	2.4%	3.33 %
Logistics & Transportation	3.3%	3.75 %
Energy & Utilities	2.4%	5.00 %
Health Care	4.1%	7.00 %
Manufacturing	13.0%	7.06 %
Construction	5.7%	7.14 %
Consumer Goods	2.4%	8.33 %
Financial Services	6.5%	27.00 %
Professional Services	17.1%	34.43 %
Retail & Wholesale	6.5%	37.00 %
Information Technology (IT)	22.8%	39.00 %
Telecommunications	4.9%	53.33 %
others	3.3%	33.75 %

Table 3. Segmentation of Industry Sectors

3.2 Assessment of Measurement Validations

The Shapiro-Wilk Test showed that the data is not normally distributed. Furthermore, we calculated the time to respond by considering the number of days between sending access to the online survey to the participants and the actual survey completion to test for non-response bias. Based on that, we compared the data of the first 25% of participants (i.e., shortest time to respond in days) with the last 25% (i.e., longest time to respond in days) (Armstrong and Overton, 1977). The Mann-Whitney-U test revealed the non-existence of significant differences. Given that studies using self-report measures to capture dependent and independent variables in the same survey might suffer from common method biases (Podsakoff et al., 2003), we included a marker variable in our survey. The results of the correlation analysis did not indicate significant correlation between the marker variable and the measurement variables. Accordingly, it can be assumed that our data does not suffer from common method bias (Lindell and Whitney, 2001).

Due to the explorative nature of our study and the non-normality of our data, we evaluated our research model by using the non-parametric Partial Least Squares (PLS) methodology following the guidelines proposed by Hair et al. (2013). Correspondingly, we first evaluated criteria for discriminant and convergent validity in order to assess our measurement model correctly. Therefore, we extracted parameters for indicator reliability, composite reliability (CR), average variance extracted (AVE) and computed Cronbach's alphas (CA) (see Table 4). With a single exception (indicator 2 of perceived benefits: 0.655), all outer loadings are above the threshold of 0.7. However, all indicator reliability values are larger than the minimum acceptable level of 0.4 and beyond that, most of them are close or above the optimal level of 0.7 (Hulland, 1999). The values of composite reliability of all constructs are well-above the threshold level of 0.7, as suggested by Bagozzi and Yi (1988). Regarding AVE, the values of all the constructs exceed the level of 0.5 (Bagozzi and Yi, 1988) and the values for Cronbach's alpha, reflecting the internal consistency of the constructs, are also all above the threshold of 0.7 (Nunnally, 1978). Moreover, according to Hair et al. (2012)'s recommendation of sample sizes in PLS, a statistical power of 80% is sufficient for a measurement model with a sample size of 123. In summary, the discriminant and convergent validity of our model can be presumed.

#	Construct	Loadings	Indicator reliability	CA	CR	Correlation to Construct # / Square root of AVE [bold]				
						1	2	3	4	5
1	Risks in-house	0.864-0.936	0.746-0.876	0.886	0.929	**0.902**				
2	Risks SaaS	0.800-0.881	0.640-0.776	0.814	0.888	-0.540	**0.852**			
3	Benefits in-house	0.706-0.858	0.498-0.736	0.704	0.832	-0.488	0.534	**0.790**		
4	Benefits SaaS	0.655-0.897	0.429-0.805	0.742	0.850	0.471	-0.605	-0.439	**0.811**	
5	Intention SaaS	0.885-0.960	0.783-0.904	0.925	0.952	0.540	-0.727	-0.522	0.720	**0.932**

Table 4. Assessment of Measurement Model

The Fornell-Larcker Criterion Analysis for checking discriminant validity (Fornell and Larcker, 1981) showed that the square root of the AVEs of each construct (highlighted bold) is greater than the correlations among the construct with any other construct in the model (see Table 4). In sum, it can be concluded that our measurement model is well-specified.

To test for multicollinearity, we calculated the Variance Inflation Factor (VIF) values. The VIFs values (Risks in-house=1.313, Risks SaaS=1.903, Benefits in-house=1.313, Benefits SaaS=1.749) are all below 5 (Hair et al., 2011). Thus, we can exclude collinearity problems for our model.

3.3 Data Analysis and Results

In order to test our hypotheses, we chose a two-step data analysis approach (see Figure 2). In the first step, we test our research model regarding the influence of reference points (attitudinal beliefs about incumbent in-house systems) on the perception of risks and benefits associated with SaaS (attitudinal beliefs about SaaS) (H1a and H1b) as well as the resulting intention to adopt SaaS (H2a and H2b). In the second step, we utilized a multi-group analysis (MGA) for analyzing whether the influence of reference points is moderated by the existing experience with SaaS applications.

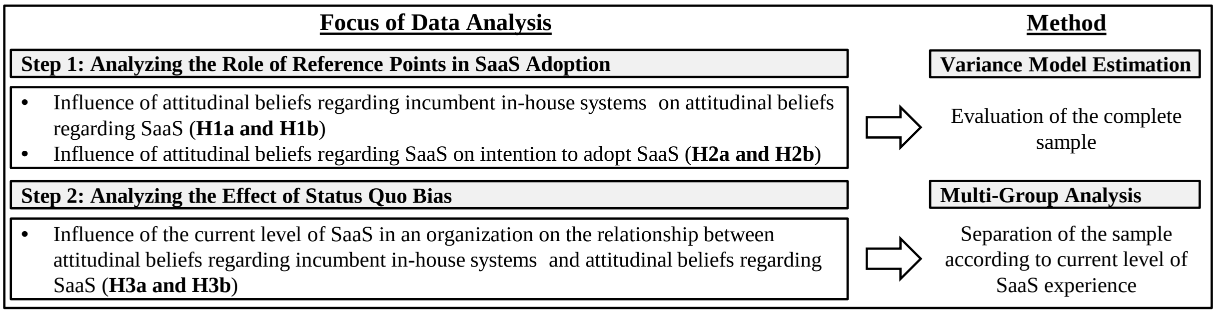

Figure 2. Data Analysis

3.3.1 Step 1: The Role of Reference Points in SaaS Adoption

To test our hypotheses H1a and H1b as well as H2a and H2b, the effect sizes and significance of path coefficients were evaluated based on a PLS algorithm and a bootstrapping procedure (5,000 samples, no sign change option, mean replacement). The results are shown in Table 5.

We found that the perceived benefits of in-house systems are significantly negatively associated with the perceived benefits of SaaS (β=-0.451, $p<0.001$), supporting H1a. The negative relationship between the perceived risks of in-house systems and perceived risks of SaaS is also identified to be significant (β=-0.545, $p<0.001$), supporting H1b. Regarding H2a we found that the positive association of perceived benefits of SaaS with the intention to adopt SaaS is significant (β=0.439, $p<0.001$). Thus, H2a is supported. Moreover, our analysis showed that the negative association of the perceived risks of SaaS with the intention to adopt SaaS is significant (β=-0.462, $p<0.001$). Accordingly, H2b is supported as well.

Following the bootstrapping-based approach of Preacher and Hayes (2008), we found that a significant indirect effect of the perceived benefits of in-house systems on the intention to adopt SaaS through the perceived benefits of SaaS is -0.198 (p=0.006). The size of the indirect effect of the perceived risks of in-house systems on intention to adopt SaaS through the perceived risks of SaaS is significant with an indirect effect size of 0.252 (p=0.002).

In sum, the results show that our model explains 70.2% of variance in the intention to adopt SaaS (R^2=0.702), 29.7% of the variance in perceived benefits of SaaS (R^2=0.297), and 20.3% of the variance in the perceived risks of SaaS (R^2=0.203).

Relationship	**Path coefficients**	**Results**
Perceived benefits of in-house systems → perceived benefits of SaaS	-0.451***	*H1a supported*
Perceived risks of in-house systems → perceived risks of SaaS	-0.545***	*H1b supported*
Perceived benefits of SaaS → intention to adopt SaaS level	0.439***	*H2a supported*
Perceived risks of SaaS → intention to adopt SaaS	-0.462***	*H2b supported*
Significance level: ***p < 0.001		

Table 5. Results of the Variance Model Estimation

There was no significant influence of the control variables (work experience: β=0.059, p=0.427; number of decisions: β=0.009, p=0.722; self-stated responsibility for sourcing decisions: β=-0.021, p=0.512; revenue: β=0.025, p=0.598; size: β=-0.031, p=0.477; IT budget: β=0.069, p=0.439).

3.3.2 Step 2: The Effect of Status Quo Bias on Attitudinal Beliefs Regarding SaaS

In order to test H3a and H3b, we had to perform a multi-group analysis (MGA) procedure (e.g., Hair et al., 2011; Sarstedt et al., 2011). Accordingly, we separated our data set into two groups: organizations currently maintaining almost all of their enterprise applications in-house (i.e., organizations with no or a low SaaS level) and organizations that already utilize a substantial degree of SaaS (i.e., organizations with a medium or high SaaS level). We split the data sets at a marginal level of SaaS use of 5% in an organization. Accordingly, organizations that still host more than 95% of their enterprise applications in-house (n=39) are considered to have less experience with the new technology, thus, face a higher level of uncertainty when making decisions about future SaaS usage. On the other hand, organizations that already use 5% or more of their enterprise applications as a service (n=84) are assigned to the group that is expected to have a certain degree of experience with SaaS and, therefore, will base the adoption decision less on reference points (attitudinal beliefs about in-house systems). The results of the MGA are shown in Table 6. These results show that all of the hypothesized relationships in H1 and H2 are significant for both organizations with no or low SaaS experience and organizations with medium or high SaaS experience. However, the path coefficients of the relationships between perceived benefits and risks of in-house systems and perceived benefits and risks of SaaS are found to be significantly different with respect to the differences in experience with SaaS. Specifically, the negative influence of perceived benefits of in-house systems on the perceived benefits of SaaS is significantly higher for organizations that have no or low SaaS experience (β=-0.640; p<0.001) than for organizations that have medium or high SaaS experience (β=-0.379; p=0.008; MGA p=0.029). Accordingly, H3a is supported. Regarding the relationship between the perceived risks of in-house systems and perceived risks of SaaS, significant differences were found as well (MGA p=0.017). As such, the negative relationship between the perceived risks of in-house systems and perceived risks of SaaS is significantly higher for organizations with no or low experience with SaaS (β=-0.728; p<0.001) than for organizations with a medium or high level of experience with SaaS (β=-0.445; p=0.001). Therefore, H3b is supported. Differences between the two groups of organizations regarding the influence of perceived benefits and risks of SaaS on the intention to adopt SaaS were not found.

Relationship	Path coefficients		p-value of Multi-Group Analysis	Results
	Low or no SaaS experience (n=39)	**Medium or high SaaS experience** (n=84)		
Perceived benefits of in-house systems → perceived benefits of SaaS	-0.640***	-0.379***	0.029	*H3a supported*: stronger for organizations with no or low SaaS experience
Perceived risks of in-house systems → perceived risks of SaaS	-0.728***	-0.445***	0.017	*H3b supported*: stronger for organizations with no or low SaaS experience
Significance level: ***p < 0.001				

Table 6. Results of the Multi-Group Analysis

4 Discussion

Previous research has repeatedly highlighted the importance of perceived risks and benefits in organizational service innovation adoption (e.g., Benlian and Hess, 2011; Featherman and Pavlou, 2003; Wu et al., 2011). However, when analyzing decisions about replacing incumbent technologies with new technologies, it is essential to consider the complexity along with the high degree of uncertainty due to a lack of experience surrounding such decisions. Confronted with decision making under uncertainty, individuals often rely on cognitive "shortcuts", i.e., the dependence on reference points in a particular decision-making process (Shoham and Fiegenbaum, 2002). In the context of a replacement decision of an existing in-house technology with a new technology, decision makers encounter a lack of information because of lacking experience or absent historical data that induces such cognitive shortcuts. On account of this, we developed a research model that demonstrates the influence of incumbent technologies (i.e., in-house systems) on the assessment of attitudinal beliefs (i.e., perceived benefits and risks) regarding SaaS on the basis of Prospect Theory and Status Quo Bias research. In a two-step analysis, based on the data of a large scale empirical study with decision makers who are responsible for the organizational IT, we (1) identified the significant influence of reference-dependence affecting the rational weighing up of risks and benefits associated with a new SaaS technology and (2) measured the effect of the Status Quo Bias depending on the already acquired experience level of SaaS use.

We discovered that decision makers' assessments of a new SaaS technology are negatively influenced by their attitude toward the incumbent technology. In other words, if decision makers consider their incumbent system to be satisfactory because the perceived benefits outweigh the perceived risks, they will tend to form a rather negative attitude toward new, unfamiliar SaaS technologies. Vice versa, decision makers that, for example, already experienced security incidents with their incumbent technology and thus perceive higher risks associated with existing in-house solutions, will more likely display a positive attitude toward SaaS. Accordingly, decision makers who realized that their incumbent system does not offer financial benefits (any longer) will be more receptive of potential cost reductions offered by a SaaS solution and therefore, perceive benefits of SaaS higher. To conclude, the incumbent technology can exert a pronounced influence on the final SaaS adoption decision.

In addition, our results illustrate that the dependence on reference points differs significantly according to the SaaS experience in the respective organization. In contrast to previous research (Vetter et al., 2011), we are not measuring self-stated experience with SaaS according to Dibbern (2004) or Roodhooft and Warlop (1999), but rather control our study for this relationship with a defined moderator variable called SaaS experience for objective measurement. We were able to demonstrate a stronger influence of the Status Quo Bias in organizations with little to no SaaS experience. Especially, less experienced decision makers will regard the retention of the Status Quo as less risky compared to the potentially negative consequences of an adoption or replacement decision. This inaccurate assessment of risks can be regarded as a result of loss aversion, i.e., the overestimation of perceived risks of the SaaS solution. For example, decision makers could overestimate the probability and the actual consequences of down-time issues and will assess this risk more severely compared to the current risks of their incumbent system. Thus, without the necessary knowledge and past experience, a deviation from the incumbent system will be regarded as an unnecessary risk resulting in the retention of the Status Quo.

Our study offers several theoretical and practical implications. We specifically contribute to the stream of technology acceptance research by singling out the importance of reference points and Status Quo Bias in the context of SaaS adoption decisions. In particular, our study is the first using Prospect Theory to analyze decision makers' appraisals of SaaS in an organizational context by considering their evaluation of the incumbent technology they are familiar with. Moreover, our results indicate that Status Quo-Thinking is more pronounced according to the experience level indicating that adoption decisions of service innovations are potentially more affected by Status Quo Bias. Given that new organizational IT systems are almost exclusively replacement decisions, future research should consider the relevance of incumbent systems when devising their study designs. We deliberately chose a research approach based on a very generic risk-benefit assessment which could thus be adjusted according to other scenarios considering adoption, service innovation, or replacement decisions (Lee, 1999). In addition, our way of measuring the Status Quo Bias at the group level can contribute to future research as most studies so far measure Status Quo Bias with indicators such as perceived inertia or perceived sunk costs that are predominantly based on self-assessment on an individual level (e.g., Polites and Karahanna, 2012).

We also offer insights and contributions for practice. Our results indicate that providers of SaaS technologies need to adapt their business models by altering their communication and sales approach according to the respective group of potential customers. Customer groups which already passed a certain threshold in terms of their SaaS level, suffer from a less pronounced degree of Status Quo Bias and will, therefore, be easier to convince of the relative advantage of SaaS and potentially display a higher intention to adopt further solutions. Hence, providers should intend to further capitalize on their current client base with additional horizontal or vertical integration solutions. Another approach for providers that involves the current client base is customer recommendation programs. Due to the social influence on risk assessment (Lee, 2009), recommendations given by existing customers can decrease the level of uncertainty. Especially, non-adopters will demand more facts and examples to realize the relative advantage of a SaaS solution and, therefore, organized roundtables with SaaS-experienced organizations can help both SaaS providers and unexperienced decision makers to realize financial or strategic advantages. A similar way to decrease the inherent Status Quo Bias is the acquirement of further knowledge gained in workshops, lighthouse projects or extended trial versions to gain more experience with a potential new technology. From an organizational perspective, decision makers can already benefit from our study by acknowledging the influence of reference points and Status Quo-Thinking. In order to arrive at a more objective assessment of risks and benefits of both the incumbent and new technology, organizations should, therefore, encourage roundtables or group discussions. These decision-making processes should also include objective assessors such as consultants to accomplish a more objective and rational evaluation of both their incumbent system as well as a possible new SaaS solution. Furthermore, decision makers might be unaware of the difficulties their employees experience with the incumbent technology and, as a consequence, overestimate the benefits of the existing systems. This may result in a distorted perception of the new technology and, hence, obstruct an optimal adoption or replacement decision. Additional information from various parties in the organizational hierarchy might compensate for this lack of information and support an optimal decision-making process further. Against this backdrop, organizations should also scrutinize if their current company culture might encourage Status Quo-Thinking. Previous research in this context demonstrated that company culture itself can enhance Status Quo-Thinking when decision makers "reflect the imprint of cultural socialization more so than professional experience" (Geletkanycz, 1997, p. 615). According to Geletkanycz and Black (2001), a deviation from the Status Quo will be regarded even more as an unnecessary risk that could possibly jeopardize a decision maker's position in those organizations characterized by more hierarchical and traditional cultures. Interestingly, our descriptive analysis indicates indeed that more "traditional" industry sectors seem to be less likely to adopt SaaS.

Consequently, organizations and individual decision makers should realize that the Status Quo Bias might actually be an obstacle for achieving certain organizational goals, and therefore encourage processes and measures that minimize Status Quo-Thinking.

5 Limitations, Future Research, and Conclusion

As with any research, some limitations of this study merit consideration. First, our study is cross-sectional and static. IT services and systems constantly change entailing new requirements and the perceptions of new as well as incumbent technologies might change over time. As such, future research could enrich the findings of our study regarding the replacement process by measuring the assessments of different technologies longitudinally. By doing so, factors that address the Status Quo Bias, and especially factors that could quickly change the attitude toward the new technology, could be identified in order to develop appropriate countermeasures. Second, this study focuses on the top echelon's assessments of incumbent and new technologies. Even if these decision makers are ultimately responsible for the sourcing decisions in their organizations, IT decisions are often made by groups and may also be influenced by other organizational stakeholders (e.g., customers or investors). Future research can supplement our results by conducting case studies and expert interviews with decision makers at different hierarchical levels in order to fully capture the technology replacement process in organizations. In addition, the results of this study need to be verified within the context of other decisions about organizational technology adoption and in different cultural and legal settings. Decision makers in US companies or in more traditional industry sectors might display different perceptions and attitudes or draw on different reference points due to divergent company cultures than those in Europe, Asia or innovative and service-oriented industries. By way of example, a future study directed primarily at start-ups that are faced with green-field adoptions could analyze whether the attitude toward SaaS is influenced by different reference points (e.g., experience with a technology in a previous organization or recent news about security breaches). Another recommendation for future research would, therefore, encompass experiments to verify our results and to test for other effects, such as further cognitive biases in the organizational decision-making process.

To sum up, our study enhances the understanding of an organization's acceptance of SaaS technologies in particular and replacement decisions in general. When decision makers are confronted with a new technology, they frequently encounter a lack or insufficiency of data and experience. As this is often the case when assessing SaaS technologies, decision makers will draw on their experience with familiar technologies and evaluate the new technology based on their assessment of the existing one. It is essential for SaaS providers to acknowledge this relationship as they risk losing potential selling opportunities if they neglect to frame their sales strategy and marketing efforts according to these cognitive decision-making processes. Correspondingly, decision makers in organizations should be aware that their assessments of risks and the benefits associated with the incumbent technology may be skewed due to Status Quo-Thinking, which in turn, may discourage their organizations from adopting a more efficient technology and inhibiting service innovations in general. Neglecting to acknowledge these findings could have far-reaching negative consequences for overall organizational performance.

References

Ajzen, I. (1985). *From Intentions to Actions: A Theory of Planned Behavior*. Springer: Berlin Heidelberg.

Ajzen, I. and M. Fishbein (1980). *Understanding Attitudes and Predicting Social Behaviours.* Eaglewood Cliffs: Prentice Hall.

Armstrong, J. S. and T. S. Overton (1977). “Estimating Nonresponse Bias in Mail Surveys.” *Journal of Marketing Research* 14 (3)**,** 396-402.

Bagozzi, R. P. and Y. Yi (1988). “On the Evaluation of Structural Equation Models.” *Journal of the Academy of Marketing Science* 16 (1)**,** 74-94.

Bamberger, P. and A. Fiegenbaum (1996). “The Role of Strategic Reference Points in Explaining the Nature and Consequences of Human Resource Strategy.” *Academy of Management Review* 21 (4)**,** 926-958.

Bazerman, M. H. M., and A. Don (2008). *Judgement in Managerial Decision Making.* New York: Wiley.

Benlian, A. (2009). "A Transaction Cost Theoretical Analysis of Software-as-a-Service (SAAS)-based Sourcing in SMBs and Enterprises." In: *Proceedings of the 17th European Conference in Information Systems (ECIS),* Verona: Italy.

Benlian, A. and T. Hess (2010). “The Risks of Sourcing Software as a Service-An Empirical Analysis of Adopters and Non-Adopters.” In: *Proceedings of the 18th European Conference on Information Systems (ECIS),* Pretoria: South-Africa.

Benlian, A. and T. Hess (2011). “Opportunities and Risks of Software-as-a-Service: Findings from a Survey of IT Executives.” *Decision Support Systems* 52 (1)**,** 232-246.

Benlian, A., T. Hess and P. Buxmann (2009). “Drivers of SaaS-Adoption – An Empirical Study of Different Application Types.” *Business & Information Systems Engineering,* 1 (5)**,** 357-369.

Bornstein, R. F. (1989). “Exposure and Affect: Overview and Meta-Analysis of Research, 1968-1987.” *Psychological Bulletin* 106 (2)**,** 265-289.

Chau, P. Y. K. (1996). “An Empirical Assessment of a Modified Technology Acceptance Model.” *Journal of Management Information Systems* 13 (2)**,** 185-204.

Cisco (2016). *Cisco Global Cloud Index: Forecast and Methodology, 2015–2020*. URL: http://www.cisco.com/c/dam/en/us/solutions/collateral/service-provider/global-cloud-index-gci/white-paper-c11-738085.pdf (visited on 11/11/2016).

Dahlberg, T., H. Kivijärvi and T. Saarinen (2017). "Longitudinal Study on the Expectations of Cloud Computing Benefits and an Integrative Multilevel Model for Understanding Cloud Computing Performance." In: *Proceedings of the 50th Hawaii International Conference on System Sciences (HICSS),* Hawaii: USA.

David, P. A. (1985). “Clio and the Economics of QWERTY.” *The American Economic Review* 75 (2)**,** 332-337.

Davis, F. D. (1986). *A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results.* PhD Thesis. Massachusetts Institute of Technology, Sloan School of Management.

Dibbern, J. (2004). *The Sourcing of Application Software Services. Empirical Evidence of Cultural, Industry and Functional Differences.* Heidelberg: Physica-Verlag.

Eduserv (2015). *Government, Technology and the Language of Business Change.* URL: https://www.eduserv.org.uk/~/media/Insight/Reports/WEB1490%20Government%20technology%20and%20the%20language%20of%20business%20change.pdf (visited on 11/11/2016).

Eurostat (2014). *ICT Usage in Enterprises in 2014: Cloud Computing Services Used by One Out of Every Five Enterprises in the EU28.* URL: http://ec.europa.eu/eurostat/documents/2995521/6208098/4-09122014-AP-EN.pdf (visited on 11/11/2016).

Eurostat (2016). *Cloud computing - statistics on the use by enterprises.* URL: http://ec.europa.eu/eurostat/statistics-explained/index.php/Cloud_computing_-_statistics_on_the_use_by_enterprises (visited on 08/04/2017).

Featherman, M. F. and P. A. Pavlou (2003). “Predicting E-Services Adoption: A Perceived Risk Facets Perspective.” *International Journal of Human-Computer Studies* 59 (4), 451-474.

Fiegenbaum, A., S. Hart and D. Schendel (1996). “Strategic Reference Point Theory.” *Strategic Management Journal* 17 (2), 219-235.

Fleischmann, M., M. Amirpur, A. Benlian and T. Hess (2014). "Cognitive Biases in Information Systems Research: A Scientometric Analysis." In: *Proceedings of the 22nd European Conference on Information Systems (ECIS)*, Tel Aviv: Israel.

Fornell, C. and D. F. Larcker (1981). “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error.” *Journal of Marketing Research* 18 (1), 39-50.

Gartner (2016). *Gartner Says Worldwide Public Cloud Services Market Is Forecast to Reach $204 Billion in 2016*. URL: http://www.gartner.com/newsroom/id/3188817 (visited on 11/04/2017).

Geletkanycz, M. A. (1997). “The Salience of 'Culture's Consequences': The Effects of Cultural Values on Top Executive Commitment to the Status Quo.” *Strategic Management Journal* 18 (8), 615-634.

Geletkanycz, M. A. and S. S. Black (2001). “Bound by the Past? Experience-Based effects on Commitment to the Strategic Status Quo.” *Journal of Management* 27 (1), 3-21.

Gerlach, J., R. M. Stock and P. Buxmann (2014). “Never Forget Where You're Coming from: The Role of Existing Products in Adoptions of Substituting Technologies.” *Journal of Product Innovation Management* 31 (S1), 133-145.

Gewald, H. and J. Dibbern (2009). “Risks and Benefits of Business Process Outsourcing: A Study of Transaction Services in the German Banking Industry.” *Information & Management* 46 (4), 249-257.

Hair, J. F., G. T. M. Hult, C. Ringle and M. Sarstedt (2013). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* 2nd Edition. Thousand Oaks: Sage Publications.

Hair, J. F., C. M. Ringle and M. Sarstedt (2011). “PLS-SEM: Indeed a Silver Bullet.” *Journal of Marketing Theory and Practice* 19 (2), 139-152.

Hair, J. F., M. Sarstedt, C. M. Ringle and J. A. Mena (2012). “An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research.” *Journal of the Academy of Marketing Science* 40 (3), 414-433.

Hsu, C. S., S.-W. Chou and H.-T. Min (2015). “Understanding Clients’ Intentions to Explore Software-as-a-Service (SaaS) Features: A Social Capital Theory Perspective.”In: *Proceedings of the 19th Pacific Asia Conference on Information Systems (PACIS).* Singapore: Singapore.

Hulland, J. (1999). “Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies.” *Strategic Management Journal* 20 (2), 195-204.

IDC (2014). *IDC 50th Anniversary – Transformation Everywhere*. URL: https://www.idc.com/IDC_50anniversary/download/IDC50thAnn (visited on 14/04/2017).

IDC (2016). *Worldwide Public Cloud Services Spending Forecast to Double by 2019, According to IDC*. URL: https://www.idc.com/getdoc.jsp?containerId=prUS40960516 (visited on 11/11/2016).

Kahneman, D., J. L. Knetsch and R. H. Thaler (1991). “Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias.” *The Journal of Economic Perspectives* 5 (1), 193-206.

Kahneman, D. and A. Tversky (1979). “Prospect Theory: An Analysis of Decision under Risk.” *Econometrica* 47 (2), 263-291.

Kahneman, D. and A. Tversky (1984). “Choices, Values, and Frames.” *American Psychologist* 39 (4), 341-350.

Kim, H.-W. and A. Kankanhalli (2009). “Investigating User Resistance to Information Systems Implementation: A Status Quo Bias Perspective.” *MIS Quarterly* 33 (3), 567-582.

Lee, A. S. (1999). *Research MIS.* Oxford: Oxford University Press.

Lee, M.-C. (2009). "Factors Influencing the Adoption of Internet Banking: An Integration of TAM and TPB with Perceived Risk and Perceived Benefits." *Electronic Commerce Reserach and Applications* 8 (3), 130-141.

Lee, S.-G., S. H. C. Chae and Kyung M. (2013). "Drivers and Inhibitors of SaaS Adoption in Korea." *International Journal of Information Management* 33 (3), 429-440.

Levy, J. S. (1997). "Prospect Theory, Rational Choice, and International Relations." *International Studies Quarterly* 41 (1), 87-112.

Lin, A. and N.-C. Chen (2012). "Cloud Computing as an Innovation: Percepetion, Attitude, and Adoption." *International Journal of Information Management* 32 (6), 533-540.

Lindell, M. K. and D. J. Whitney (2001). "Accounting for Common Method Variance in Cross-sectional Research Designs." *Journal of Applied Psychology* 86 (1), 114-121.

McLellan, C., (2016). *SaaS in 2016: The key trends*. URL: http://www.zdnet.com/article/saas-in-2016-the-key-trends/. (visited on 14/04/2017).

Moqbel, M. A. and V. L. Bartelt (2015). "Consumer Acceptance of Personal Cloud: Integrating Trust and Risk with the Technology Acceptance Model." *AIS Transactions on Replication Research* 1 (1), 1-5.

Nunnally, J. C. (1978). *Psychometric Theory*. New York: McGraw-Hill.

Podsakoff, P. M., S. B. MacKenzie, J.-Y. Y. Lee and N. P. Podsakoff (2003). "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology* 88 (5), 879-903.

Polites, G. L. and E. Karahanna (2012). "Shackled to the Status Quo: The Inhibiting Effects of Incumbent System Habit, Switching Costs, and Inertia on New System Acceptance." *MIS Quarterly* 36 (1), 21-42.

Preacher, K. J. and A. F. Hayes (2008). "Asymptotic and Resampling Strategies For Assessing and Comparing Indirect Effects in Multiple Mediator Models." *Behavior Research Methods* 40 (3), 879-891.

Rivera, J. and R. van der Meulen (2014). Gartner Survey Reveals That SaaS Deployments Are Now Mission Critical. Stamford: Gartner. URL: http://www.gartner.com/newsroom/id/2923217 (visited on 11/11/2016).

Roodhooft, F. and L. Warlop (1999). "On the Role of Sunk Costs and Asset Specificity in Outsourcing Decisions: A Research Note." *Accounting, Organizations and Society* 24 (4), 363-369.

Roster, C. A. and M. L. Richins (2009). "Ambivalence and Attitudes in Consumer Replacement Decisions." *Journal of Consumer Psychology* 19 (1), 48-61.

Samuelson, W. and R. Zeckhauser (1988). "Status Quo Bias in Decision Making." *Journal of Risk and Uncertainty* 1 (1), 7-59.

Sarstedt, M., J. Henseler and C. M. Ringle (2011). "Multigroup Analysis in Partial Least Squares (PLS) Path Modeling: Alternative Methods and Empirical Results." In: *Measurement and Research Methods in International Marketing (Advances in International Marketing)* Ed. by Sarstedt, Schwaiger and Taylor. Bingley, United Kingdom: Emerald Group Publishing Limited, 195-218.

Schweitzer, M. (1995). "Multiple Reference Points, Framing, and the Status Quo Bias in Health Care Financing Decisions." *Organizational Behavior and Human Decision Processes* 63 (1), 69-72.

Schwenk, C. (1984). "Cognitive Simplification Processes in Strategic Decision-Making: Insights from Behavioral Decision Theory and Cognitive Psychology." *Strategic Management Journal* 5 (2), 111-128.

Shoham, A. and A. Fiegenbaum (2002). "Competitive Determinants of Organizational Risk-Taking Attitude: The Role of Strategic Reference Points." *Management Decision* 40 (2), 127-141.

Sinha, T. (1994). "Prospect Theory and the Risk Return Association: Another Look." *Journal of Economic Behavior & Organization* 24 (2), 225-231.

Slovic, P. (1975). "Choice Between Equally-Valued Alternatives." *Journal of Experimental Psychology* 1 (3), 280-287.

Synergy (2016). *2015 Review Shows $110 billion Cloud Market Growing at 28% Annually*. URL: https://www.srgresearch.com/articles/2015-review-shows-110-billion-cloud-market-growing-28-annually/ (visited on 11/11/2016).

Tversky, A. and D. Kahneman (1975). “Judgment under uncertainty: Heuristics and biases.” In: *Utility, probability, and human decision making.* Ed. by Wendt and Vlek. Dordrecht, Holland: Springer Netherlands, 141-162.

Tversky, A. and D. Kahneman (1985). “The Framing of Decisions and the Psychology of Choice.” In: *Environmental Impact Assessment, Technology Assessment, and Risk Analysis.* Ed. by Covello, Mumpower, Stallen and Uppuluri. Berlin Heidelberg: Springer Verlag, 107-129.

van der Meulen, R. and J. Rivera (2015). Gartner Says Cloud Is a Viable Option, But Not a Top Consideration for Many CIOs. URL: http://www.gartner.com/newsroom/id/3002717 (visited on 10/11/2016).

Venkatesh, V., M. G. Morris, G. B. Davis and F. D. Davis (2003). “User Acceptance of Information Technology: Toward a Unified View.” *MIS Quarterly* 27 (3), 425-478.

Vetter, J., A. Benlian and T. Hess (2011). "Setting Targets Right! How Non-Rational Biases Affect the Risk Preference of IT-Outsourcing Decision Makers - An Empirical Investigation." In: *Proceedings of the 19th European Conference of Information Systems (ECIS)*, Helsinki: Finnland.

World Economic Forum (2010). *Exploring the Future of Cloud Computing: Riding the Next Wave of Technology-Driven Transformation*. URL: http://www3.weforum.org/docs/WEF_ITTC_FutureCloudComputing_Report_2010.pdf (visited on 13/04/2017).

Wu, J.-H. and S.-C. Wang (2005). “What Drives Mobile Commerce? An Empirical Evaluation of the Revised Technology Acceptance Model.” *Information & Management* 42 (5), 719-729.

Wu, W.-W., L. W. Lan and Y.-T. Lee (2011). “Exploring Decisive Factors Affecting an Organization's SaaS Adoption: A Case Study.” *International Journal of Information Management* 31 (6), 556-563.

Zajonc, R. B. (1968). “Attitudinal Effects of Mere Exposure.” *Journal of Personality and Social Psychology* 9 (2), 1-27.