Discussion Paper

Exploring Organizational Level Continuance of Cloud-Based Enterprise Systems

by

Sebastian Walther, Saonee Sarker, Nils Urbach, Darshana Sedera, Torsten Eymann, Boris Otto

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Complete Research

Walther, Sebastian, University of Bayreuth, Bayreuth, Germany, sebastian.walther@uni-bayreuth.de

Sarker, Saonee, University of Virginia, Charlottesville, Virginia, USA, saonee.sarker@comm.virginia.edu

Urbach, Nils, University of Bayreuth, Bayreuth, Germany, nils.urbach@uni-bayreuth.de

Sedera, Darshana, Queensland University of Technology, Brisbane, Australia, d.sedera@qut.edu.au

Eymann, Torsten, University of Bayreuth, Bayreuth, Germany, torsten.eymann@uni-bayreuth.de

Otto, Boris, TU Dortmund University, Dortmund, Germany, boris.otto@tu-dortmund.de

Abstract

As cloud computing has become a mature technology broadly being adopted by companies across all industries, cloud service providers are increasingly turning their attention to retaining their customers. However, only little research has been conducted on investigating the antecedents of service continuance in an organizational context. To address this gap in research, we carried out a quantitative-empirical study. We developed a conceptual model that builds on previous research on organizational level continuance. We tested this model, using survey data gathered from IT decision makers of companies which have adopted cloud enterprise systems. The data was analyzed using PLS. The results show that continuance intention can be predicted both by socio-organizational and technology-related factors, explaining 55.9 % of the dependent variable's variance. Besides cloud specific findings, the study also enhances knowledge in the area of organizational level system continuance as well as its connection to IS success.

Keywords: Cloud Computing, Enterprise Systems, Organizational-level Analysis, Organizational Benefits, IS Success, Software as a Service.

1 Introduction

A growing trend in today's enterprise applications market is the installation of cloud-based enterprise systems (ES). From consumer goods companies, such as Starbucks, to financial service companies, such as Allianz, more and more companies are implementing cloud-based ES for specific lines of businesses, such as human resource management (e.g. SuccessFactors) or customer relationship management (e.g. Salesforce.com). In addition, there are also a wealth of functionally integrated enterprise resource planning (ERP) service offerings (e.g. SAP Business ByDesign), which now make sophisticated ERP systems affordable to small and medium sized enterprises (Salleh et al., 2012). Cloud-based ES are a specific form of software as a service (SaaS), with SaaS being an application provided to the consumer running on a cloud infrastructure (Mell and Grance, 2010). The economic importance of SaaS and, more specifically, cloud-based enterprise applications can best be expressed in financial figures: in 2015, SaaS revenue is expected to reach $22.1 billion (Gartner, 2012), with cloud-based enterprise applications accounting for 13.1 % of the overall enterprise application software market (2010: 9.6%) (Gartner, 2011).

A systematic literature review on SaaS (which considered the AIS basket of 8 journals and proceedings of major conferences such as ICIS and ECIS) that we carried out using the search terms “SaaS” and “software as a service” has shown that there is a rich and steadily expanding body of literature investigating the drivers of SaaS adoption. More specifically, research on SaaS adoption has mainly been focused on the circumstances under which organizations introduce SaaS. As SaaS is considered a special form of IT sourcing, empirical and conceptual research has been based on the theoretical perspectives of classical IT outsourcing, such as the resource-based view (Xin and Levina, 2008) or transaction cost theory (Susarla et al., 2009). Being a relatively new phenomenon, research on SaaS in later phases of the software lifecycle, such as the continuance or discontinuance of SaaS, is sparse. Accordingly, only two conceptual papers (Walther and Eymann, 2012; Wang, 2011) and one empirical paper (Benlian et al., 2011) could be identified in the course of the literature review, dealing with SaaS continuance. But not only SaaS has seen a lack of research concerning later phases of the software lifecycle: also research on ES in general has been neglected (Esteves and Bohoquez, 2007). The lack of research regarding the central concept of continuance of cloud-based ES is surprising, as cloud computing service models are mostly subscription-based (Mell and Grance, 2010), with the “theoretical” possibility of instant service cancellation on the part of the customer without needing to fear any penalties. This opposes classical on-premise ES, which usually are based on long-term license-based payment models, where IT decision makers can be “locked in” due to contractual design. This is also reflected in stories about SaaS providers having problems in retaining their customers (e.g. Salesforce.com), when SaaS was initially adopted but quickly replaced even at an early stage of usage.

So research on continuance of operational cloud-based ES has both a practical and an artifact-specific motivation. On the other hand, organizational level continuance has also been an under-researched field as far as theory is concerned, where “continuance research has generally been conducted on the level of individual users, while organizational [dis-]continuance decisions are typically made by senior IS executives or others in the firm who may not be intense users of the system in questions. Decisions made by these executives can be impacted by a wide range of factors likely to have limited relevance to individual users, such as the need to accommodate changes in strategic direction or the need to respond to pressures to reduce organizational costs” (Furneaux and Wade, 2011). Therefore, to contribute to the empirical evidence of organizational level continuance, we took a socio-technical approach. Our research model was validated using a sample of senior IT decision makers reporting on their organizational and group properties concerning cloud-based ES. This stands in contrast to recent empirical work, such as Benlian et al. (2011) who explain organizational level continuance of SaaS by applying individual level mechanisms known from social psychology. So the central research question of this study is:

“What factors influence the organizational level continuance of cloud-based ES?”

To answer this question, we apply a quantitative-empirical research design which is organized as follows. First, we present our theoretical framework, including a literature review on IS continuance and IS success. Second, the hypotheses are developed. Third, we describe our methodology, including the development of the measurement instrument and the selection of the data analysis method. Finally, the results of the quantitative assessment are presented and discussed.

2 Theoretical Framework

Given the absence of a strong organizational level *continuance* theory, we structured our a-priori model according to the *discontinuance* model as suggested by Furneaux and Wade (2011). Therefore, analogously to “change forces” (e.g. system performance shortcomings), we identified “continuance forces" as well as "continuance inertia" which were predicted to positively influence continuation intention. In this process, we took a socio-technical approach, identifying system quality and information quality as technology-related, and net benefits as socio-organizational *continuance forces*, arguing that a good way to predict continued use of information systems is to evaluate their level of operational success. In addition, to keep our model coherent, we identified technical integration as technology-related, and system investment as socio-organizational *continuance inertia*. The framework is grounded at the organizational level of analysis (Rousseau, 1985), whereas the object of analysis is that of an individual ES.

2.1 Adoption, Continuance, and Discontinuance

Literature on adoption, continuance, and discontinuance from an individual perspective has mainly been based on theories drawing upon cognitive and social psychology, such as expectancy-value theory (Fishbein and Ajzen, 1975) or theory of planned behavior (TPB) (Ajzen, 1991). Based on this, research on adoption of IT artifacts with regard to individuals has mainly evolved around the technology acceptance model (TAM) (Davis, 1989), whereas individual level continuance of IT artifacts has mainly been studied using expectation-confirmation theory (ECT) (Oliver, 1980), which has taken shape in the expectation-confirmation model (ECM) (Bhattacherjee, 2001) and its popular extensions (e.g., Bhattacherjee et al., 2008) in IS research. In contrast to the rich body of both adoption and continuation research of individuals, research on organizational level continuance and discontinuance is still sparse (Furneaux and Wade, 2011; Jeyaraj et al., 2006). This complementary stream of research has investigated organizational level adoption, continuance, and discontinuance building on paradigms such as the technology-organization-environment framework (TOE) (Tornatzky and Fleischer, 1990), diffusion innovation theory (DOI) (Rogers, 1983), or social contagion (Teo et al., 2003). According to Jeyaraj et al. (2006), the quantity and speed of innovation adoption and diffusion in organizations is dependent on innovation characteristics (factors that describe the innovation, such as communicability or ease of use), organizational characteristics (such as administrative intensity or costs), and, finally, environmental characteristics (like industry type, maturity or market competition). Their view suggests that research on organizational level adoption has mainly investigated the question under which structural *predispositions* organizations adopt a specific IT artifact. In contrast, our work focuses on factors which lead to the continuance of operational information systems, implying that the performance and success of a system can be evaluated – in contrast to the pre-adoption phase, where only expectations are available to predict use. This has far-reaching implications for model development, as it allows integrating post-adoption variables as predictors of continued information systems use.

2.2 Continuance Forces: Information Systems Success

Research on information systems success has a long tradition and has come up with a number of theoretical and empirical contributions. Within this body of research, the IS success model (DeLone and McLean, 1992) and its revision (DeLone and McLean, 2003) have evolved as predominant frameworks to structure IS success (Urbach et al., 2009). This model is used in the following for four reasons. First, the IS success model has been applied in several contexts, such as e-commerce success (Wang, 2008), enterprise systems success (Gable et al., 2008), or to evaluate the success of employee portals (Urbach et al., 2010). Second, due to the categories being quite comprehensive, the results are easy to communicate. Third, it is the most widely used success measurement framework and therefore provides a high degree of external validity. And fourth, the IS success model has proven to be able to represent ES specific (Gable et al., 2008) and SaaS specific (Walther et al., 2012) success dimensions in an exhaustive manner. The revised IS success model consists of six inter-related variables: information quality, service quality, system quality, use, user satisfaction, and net benefits. In our study, however, we do not draw upon the hypotheses network as suggested by the IS success model, but we focus on socio-organizational and technology-related variables to measure dimensions of success. Therefore, we excluded three of the variables from our analysis: (1) user satisfaction, as it is an individual, affective response connected to operational users of the information system, and as satisfaction has often been discussed for not representing success per se, but rather being a result of a successful information system (Gable et al., 2008); (2) use, as it refers to single operational users and is therefore not suited as a success variable in the research context outlined; and (3) service quality, which would lead to confusion in the context of cloud services, as it can be confounded with cloud service quality, instead of helpdesk service quality as proposed by Delone and McLean (2003).

2.3 Continuance Inertia: Commitment

Complementary to our efforts to find socio-organizational and technology-related variables of success, we identified additional factors influencing organizational persistence, especially for the context of cloud-based ES. This led to the inclusion of system investment as socio-organizational commitment and technical integration as technological commitment (see Furneaux and Wade, 2011). Both commitments are particularly interesting in the light of cloud computing. The importance of system investment, as a source of behavioral persistence, has often been labeled as “sunk cost phenomenon” (Arkes and Blumer, 1985), with managers tending to make consecutive investments despite the fact that rational reasons for discontinuance exist. More recent work on system investment has studied its role in the formation of computer software prices when switching between software solutions (Ahtiala, 2006), as well as its impact in consecutive IT outsourcing decisions (Benlian et al., 2012). System investment is an interesting variable in the light of cloud computing, as one major cloud computing benefit often stated in research and practice is its “low entry barriers” and “low upfront cost” (Armbrust et al., 2010). This suggests that cloud services, which have been described as “utility computing on a commercial basis” (Armbrust et al., 2010), can easily be turned on and off, similar to a telephone system, as outlined by McCarthy in 1961 (Wei and Blake, 2010). This stands in contrast to the fact that ES usually bring about large implementation costs, which would imply that system investment plays a significant role in the continuance of cloud-based ES. Technical integration, the second factor, refers to the fact that enterprise software is usually operated within a large network of services, applications, servers, etc., with the management of interdependencies and *complexity* being one of the main tasks of IT managers. In this context, Swanson and Dans (2000) have shown the unwillingness to discontinue tightly integrated systems, as any change would usually impact a variety of related components. While the technical flexibility of cloud computing has been highlighted by several authors Bibi et al. (2012), which might reduce the role of technical integration, several studies have suggested that ES are complex information systems (Ko et al., 2005), with a substantial complexity due to the representation of cross-functional business processes (Davenport and Short, 1990) and the imperative to integrate various application types via sophisticated enterprise application integration software (e.g. SAP NetWeaver Process Integration). Therefore, technical integration appears a relevant variable in the context of cloud-based ES.

3 Hypotheses Development

In this section we present the hypotheses development, considering the assumed relationships between both continuance forces as well as continuance inertia and continuance intention as our final dependent variable. The resulting research model including the hypotheses to be tested is shown in Figure 1.

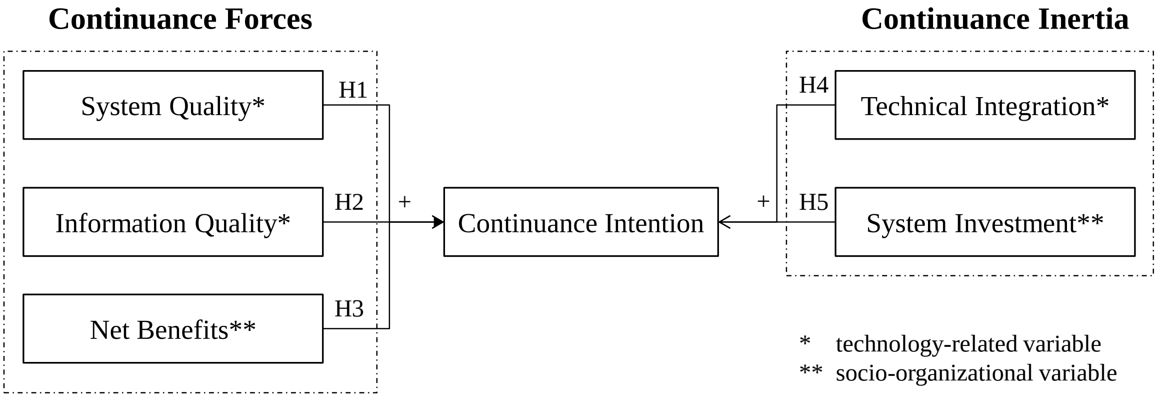

Figure 1. Research Model

3.1 Continuance Forces

We define continuance forces as factors which actively influence the perpetuation of the status quo. In this study, we assume that the strongest argument for continuing a system is its operational success. Hence, in order to keep our model coherent within our socio-technical approach, we investigate two technical success measures (information quality and system quality) and one socio-organizational success (net benefits).

System Quality

System quality, being the most desirable characteristic of an information system (DeLone and McLean, 2003), reflects certain system properties, such as processing power, reliability, or ease of use. System quality has a strong impact on the workflows of operational system users, as the input and output of data is interwoven into daily business (i.e. system failure, such as the infamous “blue screen”, might interrupt work in progress or even lead to loss of data). In addition, a system which is difficult to use might use up a significant amount of human resources, which could be better distributed and utilized elsewhere. Hence, poor system quality can lead to consumption of valuable company resources. As the IT function is responsible for problems caused by IT failure, it will try to ensure high system quality. If a system cannot provide these requirements, it is likely to be replaced (Furneaux and Wade, 2011). The relationship between continuance and system quality has gathered mixed empirical support (Petter et al., 2008) on an organizational level. However, it has not been tested in the context of SaaS or ES. It was therefore hypothesized that

H1: System quality is positively correlated with continuance intentions.

Information Quality

Information quality is the most desirable characteristic of system output (DeLone and McLean, 2003), referring to aspects such as format, timeliness, or comprehensibility. One of the main tasks of ES is the provision of information for strategic, management, and operational needs within a company (Anthony, 1965). Poor information quality can harm the company on several organizational levels. For instance, operational users of the system are dependent on an adequate format of the data, as transferring data between input interfaces can consume considerable time when formats are incompatible. In addition, strategic decisions are often based on an aggregation and analysis of fundamental data, with the quality of the information significantly affecting executives in their organizational behavior. If the system is not capable of providing relevant and properly formatted data, executives might give this pressure down to the IT function, which will be forced to replace the information system. There is no sufficient empirical evidence for the relationship between information quality and continuance intention so far (Petter et al., 2008). Thus, it was hypothesized that

H2: Information quality is positively correlated with continuance intentions.

Net Benefits

Net benefits is the extent to which an information system is beneficial to individuals, groups, and organizations (DeLone and McLean, 2003). The main task of an information system is to support the company in its business processes. Hence, an information system is only a means to an end, such as profitability. The failure to support business processes, help to raise productivity or the exposure to risks due to the information system therefore have to be seen as essential parts whether an ES is continuously used. Hence, failure to support company goals on the part of an information system might lead to discontinuance of this system. There is some empirical evidence for the relationship between net benefits and continuance intention (Petter et al., 2008). However, this relationship has not been tested in the context of SaaS. Therefore, it was hypothesized that

H3: Net benefits are positively correlated with continuance intentions.

3.2 Continuance Inertia

We define continuance inertia as sources which positively influence the continuance of information systems. In our study, this is represented by technical integration of the system and system investment as socio-organizational commitment analogously to the work of Furneaux and Wade (2011).

Technical Integration

Technical integration is defined as the "extent to which an information system relies on sophisticated linkages among component elements to deliver required capabilities" (Furneaux and Wade, 2011). Despite the vision of seamless service-orientation and modern ERP systems, information systems are usually embedded within an interwoven network of information technology. These interrelations between operational systems are often not well documented, leading to unpredictable system performance when a system is replaced. In addition, replacement intentions are usually formed more easily with regard to systems with a low complexity, as high complexity and integration increases the likelihood of difficulties when the system is discontinued (Furneaux and Wade, 2011), resulting in performance shortcomings which can severely damage daily business. Thus

H4: Technical integration is positively correlated with continuance intentions.

System Investment

System investment is defined as "the financial and other resources committed to the acquisition, implementation, and use of an information system" (Furneaux and Wade, 2011). Implementing and maintaining an information system is usually associated with a variety of investments, such as capital and human resource investments. Therefore, discontinuance of an information system is usually associated with a short-term loss of company resources, which in turn is associated with additional costs for implementing the replacing system. In addition, IT decision makers have expressed their feeling of "wasting" resources (Furneaux and Wade, 2011) when discontinuing a system. Thus, we hypothesize that

H5: System investment is positively correlated with continuance intentions.

4 Methodology

Quantitative methods, particularly surveys, are considered superior to qualitative approaches with respect to generalizability (e.g., Johnson and Duberley, 2000). For this reason, we carried out a survey to collect data for our theoretical model's empirical assessment.

4.1 Instrument Development

To test the research model, we used both formative and reflective measures (see Table 1). The items were measured on a 7-point Likert scale, ranging from "strongly disagree" to "strongly agree". Continuance forces were measured formatively, as formative measurement provides "specific and actionable attributes" of a concept (Mathieson et al., 2001), which is particularly interesting from a practical viewpoint. In formative measurement, the weight of single indicators can be used to draw practical implications on the importance of specific details and therefore guide practical enforcement on these system characteristics (e.g. "overall system quality is high" (reflective) vs. "system is easy to use" (formative)). Another possibility of modeling "actionable attributes" would have been the use of multi-dimensional constructs, where first-order constructs (dimensions) can be measured reflectively (e.g., Wixom and Todd, 2005). However, taking the IT decision makers' time constraints into account, this approach would have been rather impracticable, as it would have raised the number of questions by the number of three (assuming three indicators per first-order construct). Unlike continuance forces, which represent the evaluation of an information system's success, continuance inertia can be seen as historically given. Measuring these constructs formatively would add little to the practical contribution of the study. Therefore, these constructs were measured using well-validated reflective scales (Furneaux and Wade, 2011). The formative instrument was developed considering the recommendations of Moore and Benbasat (1991) with elements of more recent scale development procedures (Diamantopoulos and Winklhofer, 2001; MacKenzie et al., 2011; Petter et al., 2007).

In the conceptualization and content specification phase, we clearly defined the constructs and identified SaaS specific success measures by conducting a content-based systematic literature review considering the recommendations of Webster and Watson (2002). To these newly identified SaaS specific measures, we added existing ES success measures (Gable et al., 2008) and general IS success measures (Wixom and Todd, 2005). This led to an initial set of 39 net benefits, 8 information quality and 21 system quality measures. This initial set was then reduced by culling or dropping items which seemed too narrow or not significant in our context of investigation. Based on this identification of the relevant dimensions, we then generated an item pool which represented all aspects of the construct, while "minimizing the extent to which the items tap concepts outside of the domain of the focal construct" (MacKenzie et al., 2011). As "dropping a measure from a formative-indicator model may omit a unique part of the conceptual domain and change the meaning of the variable, because the construct is a composite of all the indicators" (MacKenzie et al., 2005) and keeping "irrelevant items" will not bias the results when analyzing the data using PLS (Mathieson et al., 2001), all initially identified dimensions were kept and transformed into items. Content validity, which is the "degree to which items in an instrument reflect the content universe to which the instrument will be generalized" (Straub et al., 2004), was assessed using the Q-sorting procedure, which, according to Petter et al. (2007), is one of the best methods to ensure content validity for formative indicators. In this effort, we followed a two-round procedure. In the first round we gave a list of the previously created items and construct definitions to a group of four researchers. The participants then had to match the items to the different constructs. The first round showed a low average hit ratio of 0.67 and a Cohen's Kappa (Cohen, 1968) of 0.63. After identifying and changing problematic items (e.g. wording, intersection between items), this procedure was repeated. In the second round the hit ratio rose to 0.85 and Cohen's Kappa was clearly above the recommended threshold level of 0.65 (e.g., Todd and Benbasat, 1992). After this round, two more items were modified.

Construct	Definition	Literature Sources
System Quality (Formative)	The desirable characteristics of a system, e.g. ease of use, reliability, response time, etc.	(Bailey and Pearson, 1983; DeLone and McLean, 1992; DeLone and McLean, 2003)
Information Quality (Formative)	The desirable characteristics of system output, e.g. completeness, format, relevance, etc.	(Bailey and Pearson, 1983; DeLone and McLean, 1992; DeLone and McLean, 2003)
Net Benefits (Formative)	The extent to which an information system is beneficial to individuals, groups and organizations.	(DeLone and McLean, 1992; DeLone and McLean, 2003)
System Investment (Reflective)	The financial and other resources committed to the acquisition, implementation, and use of an information system.	(Furneaux and Wade, 2011; Gill, 1995; Keil et al., 2000)
Technical Integration (Reflective)	The extent to which an information system relies on sophisticated linkages among component elements to deliver required capabilities.	(Furneaux and Wade, 2011; Swanson and Dans, 2000)

Table 1. Constructs and Definitions

The pretest was carried out to have a first test of the complete instrument, especially concerning wording, length, and instructions (Moore and Benbasat, 1991). The questionnaire was distributed to sales and consulting divisions of one of the largest cloud service providers worldwide, as well as to a group of researchers. The survey was distributed online. Below each question page a textbox was given, allowing the participants to freely comment on issues arisen. 19 questionnaires were completed in this phase. As a result, a few changes were made, such as shortening the introductory text and re-wording of “my cloud enterprise system” to “our cloud enterprise system” to highlight the organizational character of the study. The quantitative evaluation of the formative measurement model is described in the subsequent section.

4.2 Data Collection

The survey was carried out in a period of five months. It was made available as an online questionnaire, on paper, and as an interactive PDF file. It was distributed over several distribution channels, such as social media channels of cloud service providers, or it was directly made available to IT decision makers having adequate backgrounds (e.g. via business networks like LinkedIn and XING). After dropping 23 invalid questionnaires, 115 questionnaires were used to test the research model (see Table 2).

Position in Company	#	# Employees	#	System Age	#
Top Management	52	1-99	35	1-6 months	26
IT Executive	34	100-249	14	7-12 months	29
Line of Business Manager	17	250-499	29	13-18 months	36
IT Personnel	10	500-999	16	18+ months	24
Others (e.g. IT strategy)	2	1000+	21		

Table 2. Sample Characteristics

Due to the methodology of the survey, individuals reported on organizational or group properties. It was therefore important to make sure that the participants possessed adequate knowledge. Hence, we applied the key informant approach (Segars and Grover, 1998). This included a note in the introduction part of the questionnaire that the study addresses key decision makers, and a specific question at the beginning of the questionnaire asking if the participant is involved in the decision whether or not the ES should be continued. In addition, in an effort to increase content validity, we asked the participants to fill out the questionnaire with regard to one specific type of ES only. Due to the distribution method via social media platforms, the response rates could not be calculated reliably. However, to address the possibility of response rate bias, we used a stratified sample of IT decision makers.

4.3 Data Analysis

The data was analyzed using SmartPLS Version 2.0.M3 (Ringle et al., 2005) and SPSS. SPSS was used to calculate variance inflation factors and to run additional exploratory factors analysis. We chose a variance-based approach to analyze the structural model for four reasons. First, the partial least squares (PLS) approach is well suited to analyze small to medium sample sizes, providing parameter estimates at low sample sizes (Chin et al., 2003; Hulland, 1999). Second, PLS is more appropriate for exploratory research (Gefen et al., 2011), especially to explore new structural paths within incremental studies which build on prior models (Chin, 2010). Third, due to its variance-based approach, PLS is better suited for predictive application. As the goal of the study was to find drivers of organizational level continuance, and not to test a specific behavioral model, PLS is adequate in this context. Fourth, continuance forces were measured formatively, which is adequately supported by PLS (Urbach and Ahlemann, 2010).

5 Results

The PLS estimates were reported according to recommendations provided by Hair et al. (2011) as well as in a 2-step approach as outlined by Chin (2010). The measurement model and the path model were both analyzed with parameter settings using 115 cases and 5,000 samples (Hair et al., 2011). Missing values were replaced using the “mean replacement” algorithm supported by SmartPLS.

5.1 Measurement Model

The reflective measurement model was assessed by estimating internal consistency, as well as discriminant and convergent validity (see Table 3). The instrument showed satisfactory reliability, as reflective factor loadings were all above 0.64, which is clearly above the proposed threshold level of 0.5 (Hulland, 1999). Composite reliability also was adequate, with all constructs being above 0.85 (Nunnally and Bernstein, 1994).

Continuance Intention* (reflective) (Adapted from Bhattacharjee 2001)		**loadings**	**t-value**	**AVE**	**Composite Reliability**
				0.74	**0.85**
CI1	We intend to continue the subscription of our cloud enterprise system rather than discontinue its subscription.	0.866	12.300		
CI2	We intend to continue the subscription of our cloud enterprise system than to subscribe to any alternative means.	0.853	18.727		
Technical Integration (reflective) (Adapted from Furneaux and Wade 2011)		**loadings**	**t-value**	**AVE**	**Composite Reliability**
				0.89	**0.96**
TI1	The technical characteristics of the system make it complex.	0.931	19.343		
TI2	The system depends on a sophisticated integration of technology components.	0.964	22.714		
TI3	There is considerable technical complexity underlying this system.	0.938	18.156		
System Investment (reflective) (Adapted from Furneaux and Wade 2011)		**loadings**	**t-value**	**AVE**	**Composite Reliability**
				0.73	**0.89**
SI1	Significant organizational resources have been invested in this system.	0.641	2.253		
SI2	We have commited considerable time and money to the implementation and operation of the system	0.947	3.148		
SI3	The financial investments that have been made in this system are substantial.	0.946	3.120		

* One item was dropped due to poor psychometric properties.

Table 3. Quantitative Assessment of Measurement Model (Reflective)

Convergent validity was established as average variance extracted (AVE) of all constructs was clearly above 0.5 (Fornell and Larcker, 1981). All square roots of each AVE were higher than the corresponding latent variable correlations, showing a desirable level of discriminant validity (see Table 4).

Latent Construct	1	2	3	4	5	6
1. System Quality	**formative**					
2. Information Quality	0.68	**formative**				
3. Net Benefits	0.63	0.54	**formative**			
4. Technical Integration	-0.15	-0.05	-0.16	**0.89**		
5. System Investment	-0.28	-0.07	-0.25	0.68	**0.73**	
6. Continuance Intention	0.68	0.52	0.56	-0.28	-0.16	**0.74**

Note: The diagonal (bold) shows the construct's square root of AVE

Table 4. Discriminant Validity

Formative measures were assessed using the 3-step procedure proposed by Hair et al. (2013) (see Table 5). In a first step, convergent validity was assessed, which is the "extent to which a measure correlates positively with other measures of the same construct" (Hair et al., 2013). In other words, formative constructs should highly correlate with reflective measures of the same construct. This test is also known as redundancy analysis (Chin, 1998). All constructs showed adequate convergent validity, with path strengths ranging from 0.82 to 0.87, which is above the recommended threshold level of 0.8 (Chin, 1998). The reflective set showed adequate convergent validity, with values above 0.96. The second step includes the assessment of the measurement model for collinearity issues, which was done by calculating the variance inflation factors (VIF) of each indicator. All VIFs showed to be clearly below the recommended threshold level of 5 (Hair et al., 2013). In a third step, indicators were assessed for significance and relevance employing the full research model. Several formative indicators were not significant at the p=0.1 level. However, this is not surprising, since, according to Cenfetelli and Bassellier (2009), the higher the number of indicators is, the more likely is it that these indicators are non-significant, as several indicators "compete" to explain the variance in the target construct. In their seminal article, Mathieson et al. (2001) employ seven formative indicators to measure perceived resources, of which four are insignificant. In our study, system quality shows three indicators to be significant at the p=0.1 level, whereas information quality only shows one indicator to be significant. Net benefits shows two indicators to be significant. Cenfetelli and Bassellier (2009) note that the non-significance of indicators should not be misinterpreted as irrelevance. It means only that these indicators have a smaller influence on the target construct than other indicators do (weight). Another problem is the occurrence of negative indicator weights (Cenfetelli and Bassellier, 2009), which should not be interpreted as the item having negative impact on the construct, but that it is more highly correlated with indicators of the same measure than with the construct it measures. To handle insignificant and negative indicators, we followed a procedure recommended by Hair et al. (2013) to eliminate problematic items by assessing both, significance and loadings of the items. While the weight of an item indicates its relative importance, loadings represent the absolute contribution of the indicator. In other words, an indicator can be relatively unimportant, however, when "stronger" indicators are deleted or not available, these indicators can still give a good estimation if the loadings are high. The detailed procedure to eliminate problematic items proposed by Hair et al. (2013) was subsequently applied. All outer loadings are above 0.5, except for the items NB8 (Innovation Ability) and NB11 (IT staff requirements). Both indicators' loadings are significant, hence they are kept.

Redundancy Analysis, Assessing Multicollinearity, Significance and Contribution					
Net Benefits (formative)		**VIF**	**t-value**	**weights**	**loadings**
Our cloud enterprise system…					
NB1	… increases the productivity of end-users.	3.696	0.160	0.034	0.751
NB2*	… increases the overall productivity of the company.	3.557	2.078	0.485	0.806
NB3*	… enables individual users to make better decisions.	1.875	1.786	0.342	0.660
NB4	… helps to save IT-related costs.	2.912	1.072	0.287	0.515
NB5	… makes it easier to plan the IT costs of the company.	2.475	1.474	-0.308	0.331
NB6	… enhances our strategic flexibility.	3.923	0.595	-0.153	0.492
NB7	… enhances the ability of the company to innovate.	3.559	1.278	-0.331	0.313
NB8	… enhances the mobility of the company's employees.	2.855	0.342	0.082	0.657
NB9	… improves the quality of the company's business processes.	2.156	0.918	0.235	0.593
NB10	… shifts the risks of IT failures from my company to the provider.	1.888	1.495	0.328	0.562
NB11	… lower the IT staff requirements within the company to keep the system running.	1.708	0.539	0.141	0.365
NB12	… improves outcomes/outputs of my company.	1.955	0.504	0.122	0.514
Net Benefits (reflective) (Adapted from Wixom and Watson (2001))		**f^2**			
Redundancy Analysis		0.815			
NB13	… has changed my company significantly.		23.901		0.903
NB14	… has brought significant benefits to the company.		91.381		0.938
System Quality (formative)		**VIF**	**t-value**	**weights**	**loadings**
Our cloud enterprise system…					
SQ1#	… operates reliabliy and stable.	1.570	0.729	0.088	0.530
SQ2#	… can be flexibly adjusted to new demands or conditions.	2.463	1.399	0.257	0.785
SQ3#	… effectively integrates data from different areas of the company.	2.152	0.941	-0.148	0.619
SQ4#	… makes information easy to access (system accessibility).	2.201	0.093	0.015	0.574
SQ5	… is easy to use.	2.245	0.450	0.071	0.586
SQ6#	… provides information in a timely fashion (response time).	1.941	0.234	-0.035	0.515
SQ7*	… provides key features and functionalities that meet the business requirements.	2.257	2.117	0.338	0.803
SQ8*	… is secure.	1.334	2.090	0.250	0.638
SQ9	… is easy to learn.	2.308	0.342	-0.055	0.504
SQ10	… meets different user requirements within the company.	2.031	0.543	0.105	0.654
SQ11	… is easy to upgrade from an older to a newer version.	1.643	1.053	0.152	0.638
SQ12*	… is easy to customize (after implementation, e.g. user interface).	2.006	1.857	0.318	0.762
System Quality (reflective) (Adapted from Wixom and Todd (2005))		**f^2**			
Redundancy Analysis		0.808			
SQ13#	In terms of system quality, I would rate our cloud enterprise system highly.		141.426		0.969
SQ14#	Overall, our cloud enterprise system is of high quality.		136.564		0.969
Information Quality (formative)		**VIF**	**t-value**	**weights**	**loadings**
Our cloud enterprise system…					
IQ1#	… provides a complete set of information.	2.313	0.070	0.016	0.726
IQ2#	… produces correct information.	2.280	0.194	-0.054	0.661
IQ3#	… provides information which is well formatted.	2.711	0.010	-0.025	0.725
IQ4#*	… provides me with the most recent information.	2.793	1.632	0.460	0.879
IQ5	… produces relevant information with limited unnecessary elements.	2.774	1.412	0.393	0.905
IQ6	… produces information which is easy to understand.	2.903	1.491	0.317	0.841
Information Quality (reflective) (Adapted from Wixom and Todd (2005))		**f^2**			
Redundancy Analysis		0.868			
IQ7#	Overall, I would give the information from our cloud enterprise system high marks.		85.378		0.961
IQ8#	In general, our cloud enterprise system provides me with high-quality information.		69.523		0.956

Wixom and Todd (2005); * significant *at least* at the p=0.1 level

Table 5. Quantitative Assessment of Measurement Model (Formative)

5.2 Structural Model

Having established the appropriateness of the measures, we tested the model with the previously outlined parameter settings. Our model was able to explain 55.9 % of the variance in continuance intention (see Figure 2). All hypothesized paths, except for H2, showed significant relationships above $p<.05$. The highest amount of variance was explained by system quality. In contrast to our prediction, technical integration had a negative impact on continuance intention. Due to the nature of PLS calculating the path strengths, it is principally also possible that other effects had a stronger influence, hence, turning the algorithmic sign, even though the impact is generally positive. Therefore, we ran a single regression, where the sign still kept being negative. In addition to R^2 values, we also assessed predictive relevance by applying the blindfolding procedures to obtain cross-validity redundancy (Chin, 1998). The results indicated a good predictive relevance with all Q^2 being greater than 0 (Geisser, 1975), with omission distance being iterated between 5 and 10 (Hair et al., 2011).

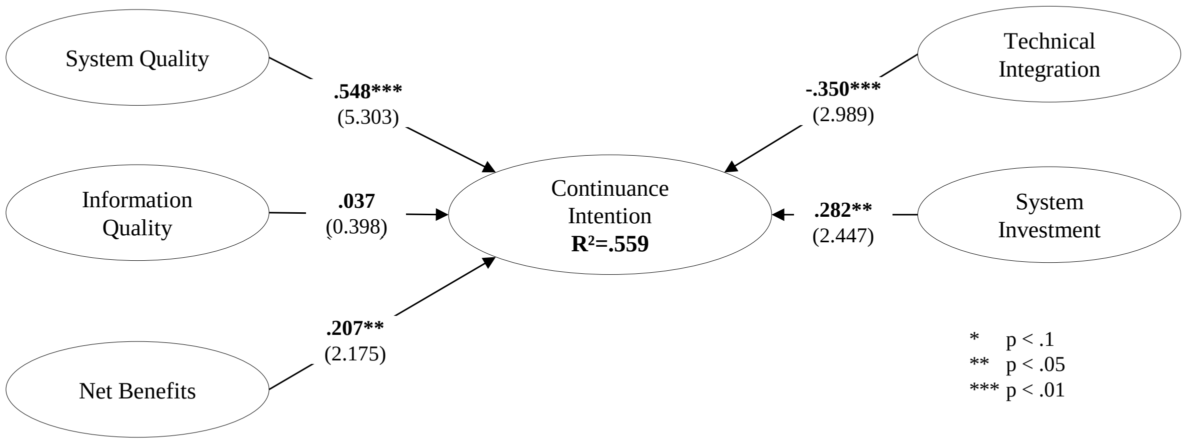

Figure 2. Results of Path Analysis

6 Discussion

The variables identified were able to explain 55.9% of the variance in continuance intention. System quality had the highest positive effect on the dependent variable, followed by system investment. Information quality showed no significant effect. The results are quite interesting, both from a practical and theoretical viewpoint. High information quality is important for all employees of the company, with different needs depending on the organizational cohort (Anthony, 1965). As outlined in the hypotheses development section, poor information quality can impact business processes throughout the company, causing severe time loss when e.g. information is presented in an improper format or is incomplete. However, the results show that continuance intention is not significantly influenced by information quality. We can only speculate why this is the case, as there has only been one study which has investigated the relationship (positive) between information quality and continuance on an organizational level (Fitzgerald and Russo, 2005). One possibility could be a high information quality in general across ES, where the IT function takes high information quality for granted. Another possibility could be that information quality is generally important, but poor information quality is perceived as relatively less important for daily business as e.g. low reliability of a system. Due to limited customer contact time, cloud service providers should emphasize the benevolence concerning system quality and net benefits. More specifically, service providers' sales personnel should emphasize that the cloud-based ES provides the key functionality needed to support business processes, that the system is secure, and that it can easily be customized. From a company benefits perspective, showing organizational productivity improvements as well as enhanced decision making capabilities should be demonstrated. What we did not predict was the negative impact of technical integration, and it is somewhat difficult to interpret this finding. Per hypothesis development, the reason why highly integrated technical systems are less likely to be discontinued is the unpredictability of system failures between highly dependent systems. The results indicate that the mechanism might be different than expected in the context of cloud computing. For instance, it might be possible that high levels of technical integration may remind respondents about the cumbersome process associated with integrating the systems, and therefore negatively affects their perceptions of (and satisfaction with) the system (Wixom and Todd, 2005). This could in turn negatively affect continuance intention. This is also in line with Leonard-Barton (1988), who found that failures occurred when developers and users were unwilling to work with the system, e.g. due to high system complexity. System complexity, as one dimension of technical integration, has also been shown to result in technostress for individual users (Ayyagari et al., 2011), which could negatively impact the willingness of an organization to continue system use. System investment influenced continuance intention significantly, as we predicted. This is not surprising, as disinvestments have been shown to be perceived as “loss” or “waste”. There are several ways to handle the sunk cost phenomenon, such as involving managers in replacement decisions which were not involved in buying decisions (Benlian et al., 2012).

From a theoretical viewpoint, the results show that framing the problem on an organizational level is adequate. According to TPB, net benefits should be interpreted as behavioral belief, similar to perceived usefulness, whereas system quality and information quality are typical external variables (Wixom and Todd, 2005). In other words, as information systems are implemented to support higher company goals, they are usually only a means to an end, i.e. to achieve company benefits. Therefore, if continuance intention was analyzed from a behavioral stance, net benefits should have the highest impact on continuance intention, as it is the main reason why a system is implemented. Hence, the results show that the process in which companies decide upon continuing a system is more complex than an individual behavioral mechanism. The study also has interesting implications for further research on adoption, continuance, and discontinuance. As the study suggests, factors from discontinuance research also impact the central concept of continuance, even at an early stage of adoption. Undoubtedly, there are numerous differences between factors influencing the use or replacement decision at different stages of the software lifecycle. Further research will have to clarify, how these different “adoption phases” are interrelated. Finally, our study makes an important contribution in understanding the role of IS success as post-adoption variables in the organizational level continuance of information systems, where surprisingly, only little research has been conducted (e.g., Petter et al., 2008; Urbach et al., 2009).

Our research has some limitations which have to be highlighted. First, it is important to note that, due to our research design, individuals report about organizational properties. It can therefore be argued that the results represent individual views rather than a shared opinion within the enterprise. Several organizational studies suffer from this possible bias, which can hardly be accessed statistically. There are two possibilities as to how future research could tackle this problem. First, a longitudinal study design would contribute to measure actual behavior, legitimating the results, if statistically relevant. This is especially relevant as the cross-sectional study design cannot test the directions of the hypotheses, which were derived theoretically only. Second, “hard data”, such as percentage of uptime or cost savings should be included into the dataset, which would also allow to reduce common method variance. Even though the study explained a reasonable amount of variance, there are several factors which also could be relevant in predicting continuance intention. For instance, Benlian and Hess (2011) have found that risk awareness concerning SaaS is still present after the system has been adopted and the actual performance can be assessed. In addition, there could be a multitude of concepts, such as environmental or institutional pressures, which might also influence the decision to discontinue existing systems. Future research will have to take additional perspectives to understand continuance on an organizational level. Third, the sub-samples of our data, such as different kinds of functional ES, implementation times, or industries might help understand structural differences. Further studies should therefore include predictive relevance between stakeholder perspectives, functional complexities of the ES, or between industries.

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