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Understanding Continuous Use of Business Intelligence Systems: A Mixed Methods Investigation

Stefan Bischoff
University of St. Gallen, Switzerland

Stephan Aier
University of St. Gallen, Switzerland

Mohammad Kazem Haki
University of St. Gallen, Switzerland

Robert Winter
University of St. Gallen, Switzerland
robert.winter@unisg.ch

Abstract:

Business intelligence (BI) systems play an important role in organizations' decision-making processes. The existing literature has long focused on the continuous use of information systems (IS). However, the specificities of BI systems such as voluntary use, long-term return of investments, heterogeneity of their use cases, and innovative rather than routine use in such systems motivate our investigating continuous use in the specific context of BI systems. To theorize continuous use of BI systems, we investigate the influencing factors and their interactions. By means of an exploratory and confirmatory mixed-methods research design that comprises a literature review, a single-case study, and a survey, we integrate the identified factors and hypothesize their influence on the continuous use of BI systems in a research model. We test the research model following a partial least squares (PLS) approach to structural equation modeling (SEM). The paper makes two primary contributions: 1) it confirms certain well-established constructs and relations in the specific context of BI systems, which are generally theorized for the continuous use of IS, and 2) it introduces either new constructs or new relations through the given investigation in the context of BI systems. Future studies can test these new constructs and relations as potential input for theorizing general IS continuous use.

Keywords: Business Intelligence, Continuous Use, Post-adoption (Post-acceptance), Mixed-methods Research.

Jan vom Brocke acted as the Senior Editor for this paper.

1 Introduction

The strategic role of business intelligence (BI) systems has become evident for many businesses since BI systems enhance organizations' management decision-making capabilities (Audzeyeva & Hudson, 2015; Negash, 2004). BI systems allow organizations to purposefully aggregate and consolidate vast amounts of data from different sources that inform operational and strategic management decisions (Negash, 2004). Even though overall information technology (IT) expenses grew by only 0.4 percent in 2013 (Gartner, 2014b), the market for BI systems has shown a much faster growth rate of 7.9 percent (Gartner, 2014a).

Despite growing investments into BI, many organizations fail to fully exploit the expected capabilities of BI systems (Audzeyeva & Hudson, 2015). BI systems' full potential can only be exploited by continuously using such systems (Audzeyeva & Hudson, 2015; Deng & Chi, 2013; Li, Hsieh, & Rai, 2013), which we focus on in this study. In line with other types of information systems (IS), the nature of BI systems implies that they cannot create value based on their pure existence. In effect, value is created while users use the system and while the system is in continuous use (Benbasat & Zmud, 2003; Gable, Sedera, & Chan, 2008). The existing IS literature sheds light on the criticality of IS continuous use to realize returns on IS investments in organizations (Bhattacherjee, 2001; Kim, Chan, & Chan, 2007; Limayem, Hirt, & Cheung, 2007; Thong, Hong, & Tam, 2006; Venkatesh, Thong, Chan, Hu, & Brown, 2011). Continuous use is a prerequisite for an information system's success, for its value contribution, and, thus, for its long-term viability (Bhattacherjee, 2001; Hsieh, Rai, & Xu, 2011). As such, the concept of continuous use is different from first-time acceptance/adoption. Research into first-time acceptance investigates IS users' initial use behavior (see, for instance, Davis' (1989) technology acceptance model (TAM)). In contrast, research into continuous use has a long-term focus and examines users' behavior and interaction with a system over a longer period of time (Bhattacherjee, 2001).

Even though the extant literature has long emphasized an IS continuous use perspective, studying continuous use in the specific context of BI systems is also important given their distinct characteristics in application and use. First, opposed to the huge amounts of transactional information systems that are used in employees' daily business, BI systems use is largely voluntary (Grublješič & Jaklič, forthcoming; Wixom & Quaadgras, 2013). Use can be considered mandatory if there is no other alternative (Hartwick & Barki, 1994), which is often not the case in the BI context since similar information can be acquired in other ways (e.g., through existing enterprise systems and spreadsheet-based analytics). As the existing IS literature already outlines, this kind of interaction significantly varies from mandatory use (Brown, Massey, Montoya-Weiss, & Burkman, 2002; Hou, 2012; Wu & Lederer, 2009), which can be based on organizational policy (Moore & Benbasat, 1991), an individual's job description, a mandate from superiors (Agarwal & Prasad, 1997), or users' being forced to use the system to be able to do their job properly (Brown et al., 2002; Wu & Lederer, 2009). Therefore, users' commitment to continuous use in the voluntary environment of BI systems becomes critical (Li, Browne, & Chau, 2006; Limayem et al., 2007).

Second, the issue of the cost-value chasm makes BI systems special from an investment perspective. Similar to other information systems, BI upfront costs are high and include huge investments in backbone infrastructure (e.g., data warehouses, data integration), training, and operations and maintenance costs (Negash, 2004). Even though organizations can forecast reductions in information systems costs from efficiencies (e.g., through their impact on operational business processes), the efficiency savings from BI systems are only a small portion of the payoff (Negash, 2004). BI systems support managerial decision making, which are long term in nature. Accordingly, their values can only be realized over a long-term

Contribution:

The contribution of this study is twofold. First, this study confirms well-established constructs and relations in the specific context of BI systems that have already been theorized for the continuous use of IS in general, such as perceived usefulness, perceived ease of use, trust, and information quality constructs. Even though the existing literature examines these constructs and their constitutive relations, our study shows the applicability of these constructs and relations in the context of BI systems with regard to their specificities. Therefore, our study reinforces the generalizability of these constructs and relations in the context of various types of information systems. Second, this study introduces either new constructs or new relations through the given investigation in the context of BI systems, such as the influence of the organization, coverage of user requirements, user support, influence of peers, and governance constructs. Researchers can use these constructs and relations for further studies on the continuous use of other types of information systems and eventually generalize to the overarching context of IS.

post-adoption period and with committed continuous use (Audzeyeva & Hudson, 2015).

Third, even though the majority of information systems provide pre-defined reports built on the transactional data of the given information system, BI systems enable users to create personalized and case-based reports and analyses based on aggregating information from different data sources (Wixom & Watson, 2010). With BI systems, users are free to define different use cases ranging from calculating credit risk, detecting financial fraud (Ngai, Hu, Wong, Chen, & Sun, 2010), managing customer loyalty/retention (Watson, Wixom, Hoffer, Anderson-Lehman, & Reynolds, 2006), selecting target groups for direct marketing campaigns on an operational level, and supporting strategic decisionss such as companies' expansion to new markets or the identification of suitable candidates for mergers and acquisitions (Wixom & Watson, 2010). As diverse as the use cases are the user groups, which have different characteristics, requirements, and preferences (Stroh, Winter, & Wortmann, 2011). Thus, the heterogeneity of use cases makes BI systems special in investigating their users' continuous use and post-adoptive behaviors.

Fourth, the distinction between routine and innovative usage behaviors is evidently dominant in BI systems compared to other types of information systems (Li et al., 2013). In effect, taking advantage of BI systems' full potential highly depends on whether their users innovatively use BI systems to better support their specific objectives, which has become more evident thanks to the changed skillset of non-technical users and the emerging trends in BI systems such as self-service BI and mobile BI. Self-service BI allows users to design and deploy their own reports and analyses that are necessary for their tasks (Pinnington, Light, & Ferneley, 2007; Spahn, Kleb, Grimm, & Scheidl, 2008). Mobile BI focuses on how data can be differently leveraged to better support decision making when in the hands of the right person at the right time (Mayer, Bischoff, Winter, & Weitzel, 2012). Therefore, innovatively using BI systems changes users' behavior and makes BI systems more differentiated and special in examining post-acceptance users' behaviors of such systems (Li et al., 2013).

The abovementioned specificities of BI systems motivate the necessity to research the continuous use of BI systems (Grublješič & Jaklič, forthcoming). Notwithstanding the necessity of examining continuous use of BI systems, a review of extant literature reveals the paucity of research in this area. Thus, we make one of the first steps towards addressing this research gap and improving our understanding of the continuous use of BI systems. We consequently derive our research question:

RQ1: What are the factors influencing the continuous use of BI systems and how do these factors interact?

To answer this research question, we opt for a mixed-methods exploratory and confirmatory research design that combines a literature review, a single-case study, and a survey[1] . The exploratory part of the study uses concurrent research methods (i.e., literature review, single-case study, and an initial survey to explore constructs and their relations). As such, the literature review reveals various constructs on IS continuous use that maybe relevant for examining continuous use of BI. Nevertheless, since these studies were not conducted in the BI context, we carry out an exploratory initial survey (exploratory factor analysis) and a single-case study to both examine the relevancy of the constructs and to explore their relations and derive hypotheses. In the confirmatory part of the study, we use a survey (including the relevant data from the initial survey in the exploratory part) and empirically tests the research model through a partial least squares (PLS) approach to structural equation modeling (SEM).

The paper proceeds as follows: in Section 2, we introduce the conceptual foundations through investigating related work. In Section 3, we then motivate and present our research design on both qualitative and quantitative aspects. In Section 4, we build the research model and motivate its constitutive hypotheses by means of evidence from case study and investigating the extant literature. In Section 5, we present the results of our quantitative data analysis. Finally, in Section 6, we conclude by discussing our findings and providing implications for practice and future research.

[1] By following a cumulative research design, this study complements an initial paper (Bischoff, Aier, & Winter, 2014) with preliminary research findings derived from the literature review, single-case study, and an initial survey. The initial paper results in exploring influencing factors on BI continuous use. In the paper at hand, we integrate the preliminary research findings into a research model through hypothesizing the relation between influencing factors and empirically confirming their interactions.

2 Conceptual Foundations and Related Work

2.1 Business Intelligence (BI) Systems

Even though the term "intelligence" has been used in artificial intelligence since the 1950s, BI systems find their root in decision support systems (DSS) and database management systems (DBMS) (Chen, Chiang, & Storey, 2012; Power, 2007). DSS emerged in the late 1960s and evolved over time in line with the state-of-the-art database technologies. Business intelligence became a popular term in the IT and business communities that built on the emerging data warehousing technologies in the 1990s (Chen et al., 2012). BI systems require specialized IT infrastructure including data extraction and analysis tools (e.g., query, reporting, data mining, forecasting, statistical analysis) and specialized databases such as data warehouses (Elbashir, Collier, & Davern, 2008; Watson & Wixom, 2007). Therefore, data warehouses are considered as the foundation of BI systems (Chen et al., 2012). BI systems are systems that "combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers" (Negash, 2004, p. 178). In the late 2000s, researchers introduced business analytics as the key analytical component of BI systems (Davenport, 2006). Chen et al. (2012) use the unified term of "business intelligence and analytics" to reflect both business intelligence and business analytics.

The use of BI systems has created a competitive advantage for many businesses (Audzeyeva & Hudson, 2015; Negash, 2004). Nevertheless, the "long-term viability of an IS and its eventual success depend on its continued use rather than first-time use" (Bhattacherjee, 2001, p. 351). Thus, we seek to understand the continuous use of BI systems.

2.2 Continuous Use of IS

Over the last few decades, organizations have significantly invested in implementing complex information systems to achieve a competitive advantage. The IS literature focuses on two main streams of research in line with the stages of IS implementation; namely, 1) IS adoption and acceptance (first-time use) (Adams, Nelson, & Todd, 1992; Agarwal & Karahanna, 2000; Agarwal & Prasad, 1998; Cooper & Zmud, 1990; Davis, 1989, 1993; Karahanna, Straub, & Chervany, 1999; Legris, Ingham, & Collerette, 2003; Moore & Benbasat, 1991; Thong, 1999; Venkatesh, Morris, Davis, & Davis, 2003) as well as (2) IS post-adoption (post-acceptance) and 2) continuous use (Ahuja & Thatcher, 2005; Bhattacherjee, 2001; Bhattacherjee, Perols, & Sanford, 2008; Jasperson, Carter, & Zmud, 2005; Kim et al., 2007; Limayem et al., 2007; Saeed & Abdinnour-Helm, 2008; Thong et al., 2006; Venkatesh et al., 2011). While the former is important for the success of a new IS, researchers have perceived the latter to be critical for realizing an IS's promised benefits (Bhattacherjee, 2001). The IS acceptance and adoption research stream, which is mainly based on the innovation diffusion theory (Rogers, 2003), the technology acceptance model (Davis, 1989), and the theory of planned behavior (Ajzen, 1991), investigates the initial adoption and intentional usage of information systems. The IS post-adoption (post-acceptance) and continuous use research stream (often synonymously called continuance), in turn, follows Bhattacherjee (2001) who defines continuous use as the long-term and ongoing (i.e., continued) use of an IS rather than the first-time use (i.e., acceptance and adoption).

Studies of continuous IS use in general have concluded with factors that influence continuous use on an abstract level. They often build on the abovementioned theories in IS acceptance so that the proposed models often reuse constructs from the established IS acceptance models (e.g., Premkumar & Bhattacherjee, 2008). Additionally, for grounding the concept of continuous use, researchers have often adapted existing theory from other domains to the IS field. The expectation-confirmation theory (ECT), for instance, which is widely used for studying consumer behavior (e.g., consumer satisfaction and post-purchase behavior) (Anderson & Sullivan, 1993; Oliver, 1980; Patterson, Johnson, & Spreng, 1997), has been adapted to IS continuous use research (Bhattacherjee, 2001). Continuous use has been studied in the context of different types of IS (e.g., social virtual worlds) (Mäntymäki & Riemer, 2012), electronic medical records (Mettler, 2012; Shaw & Manwani, 2011), the World Wide Web in general (Hsu, Chiu, & Ju, 2004), and websites in particular (Lin, Wu, & Tsai, 2005).

2.3 Continuous Use of BI Systems

Unsurprisingly, similar to IS literature, existing studies in BI literature[2] focus on two main streams of research: BI adoption and acceptance (Grublješič & Jaklič, forthcoming; Hou, 2012; Nelson, Todd, & Wixom, 2005; Popovic, Hackney, Coelho, & Jaklic, 2012) and BI post-adoption (post-acceptance) and continuous use (Audzeyeva & Hudson, 2015; Deng & Chi, 2013; Han & Farn, 2013; Li et al., 2013). Owing to the focus of our study, we summarize the studies on the continuous use of BI systems.

Deng and Chi (2013) examine continuous use of BI systems from a problem-driven perspective. They identify several constructs of system use problems; namely, reporting, data, role authorization, users' lack of knowledge, system error, and user-system interaction. They reveal that these constructs interact differently in the initial usage phase and the continued usage phase. Li et al. (2013) take a different approach and adapt the concept of rich intrinsic motivation from social psychology to the context of BI systems. They theorize two post-adoptive usage behaviors: routine use and innovative use. Drawing from motivation theory, they investigate the impact of three types of intrinsic motivations (intrinsic motivation toward accomplishment, intrinsic motivation to know, and intrinsic motivation to experience simulation) and perceived usefulness (as a key extrinsic motivator for IS use) on both routine use and innovative use. Audzeyeva and Hudson (2015) focus on the process of maximizing the long-term benefits from BI systems. They conclude that an organization's ability to exploit long-term BI benefits is influenced by its deep structure (core beliefs, organizational structures, control systems, and distribution of power) and also by its ability to overcome the effects of inertia sources that deep structure generates. Lastly, Han and Farn (2013) extend the IS continuous model that Limayem et al. (2007) propose through adding empowerment to their model. As such, they examine the impact of habit and empowerment (both psychological and structural) on BI continuous use.

To conclude, the continuous use of BI systems is a young academic discourse that started in the 2010s. Besides studies that only investigate the initial usage of BI systems (Grublješič & Jaklič, forthcoming; Hou, 2012; Popovic et al., 2012), the few existing studies on BI continuous use either merely examine system use problems (Deng & Chi, 2013), motivational aspects of BI continuous use (Li et al., 2013), and continuous use mechanisms towards expected BI benefits (Audzeyeva & Hudson, 2015), or they try to test and provide small extensions to the existing IS continuous use models (Han & Farn, 2013). According to our investigation, the factors affecting the continuous use of BI systems are not yet well understood. Except for Grublješič and Jaklič (forthcoming), who classify factors influencing initial usage of BI, the limited understanding of factors affecting the continuous use of BI systems motivates the need for researchers to theorize in this area. Therefore, we need systematic research to take into account specificities of BI systems in investigating their continuous use (Grublješič & Jaklič, forthcoming).

3 Research Design

3.1 Overall Research Design

To investigate the factors affecting the continuous use of BI systems and their interactions, we use a mixed-methods exploratory and confirmatory research design that combines a literature review, a single-case study, and a survey (see Figure 1). Mixing methods can lead to new insights and modes of analysis that are unlikely to occur if only one method is used (Kaplan & Duchon, 1988; Mingers, 2001; Venkatesh, Brown, & Bala, 2013). With this approach, we could not only learn from existing IS continuous use literature to identify influencing factors and investigate their relevance and interactions in the context of BI but also create the research model and test the derived hypotheses in an empirical setting. Therefore, we used these different methods concurrently and recursively (Venkatesh et al., 2013) to enable data triangulation (Jick, 1979). Moreover, along with concurrent research methods, we apply both exploratory and confirmatory techniques sequentially to confirm the explored interactions between the influencing

[2] To analyze prior research results in the field of BI systems, we reviewed scientific publications. We applied the following search terms: ("Business Intelligence" OR BI) and (use OR usage OR continuity OR continuance OR post-acceptance OR routinization). We chose the synonyms for the search term based on the different wording that is used for continuous use in literature; that is, continuity, continuance (Bhattacherjee et al., 2008), ongoing use (Marchand & Peppard, 2008), post-acceptance (Bhattacherjee, 2001), post-adoptive use (Cooper & Zmud, 1990), and routinization (Cooper & Zmud, 1990). We identified the related publications by scanning scientific databases (AIS Electronic Library, ACM Digital Library, DBPL, EBSCOhost, IEEE Xplore Digital Library, Science Direct, Web of Science, SpringerLink) with specific focus on the Association for Information Systems' (AIS) basket of top journals. The search revealed 30 unique results, of which eight were relevant based on a review of titles and abstracts.

factors. In effect, we follow an embedded mixed-methods design (Creswell & Plano Clark, 2011, p. 90) in which the ultimate goal is to confirm our research model through a quantitative research approach. To this end, we exploit qualitative data to explore the research model (measurement items and relations between constructs). This exploratory step also uses quantitative data (exploratory factor analysis) to support a preliminary derivation of research model's construct candidates.

In the research process, we first identified well-established items from the IS literature that may influence the continuous use of BI systems. To ensure the relevance of the extracted items in the BI context, we investigated them in a single-case study. Built on the collected and revised items, we designed and distributed a questionnaire at practitioner events to collect empirical quantitative data. To identify latent factors that influence the continuous use of BI systems, we conducted an exploratory factor analysis (EFA) based on the collected empirical data. This analysis led to ten factors: while nine factors represent influence factors of continuous use, one represents continuous use itself (see Table 4). In the subsequent step, we relied on the existing literature on IS continuous use to synthesize the relation between the explored influencing factors. Then, we used the experience gained from an in-depth single-case study in BI context to filter and hypothesize the relations among the factors and eventually to outline the research model. In effect, we motivate each of the derived hypotheses with evidence from the case study and with findings from existing literature. Based on the initial and additional quantitative data, we tested the research model by following a partial least squares (PLS) approach to structural equation modeling (SEM).

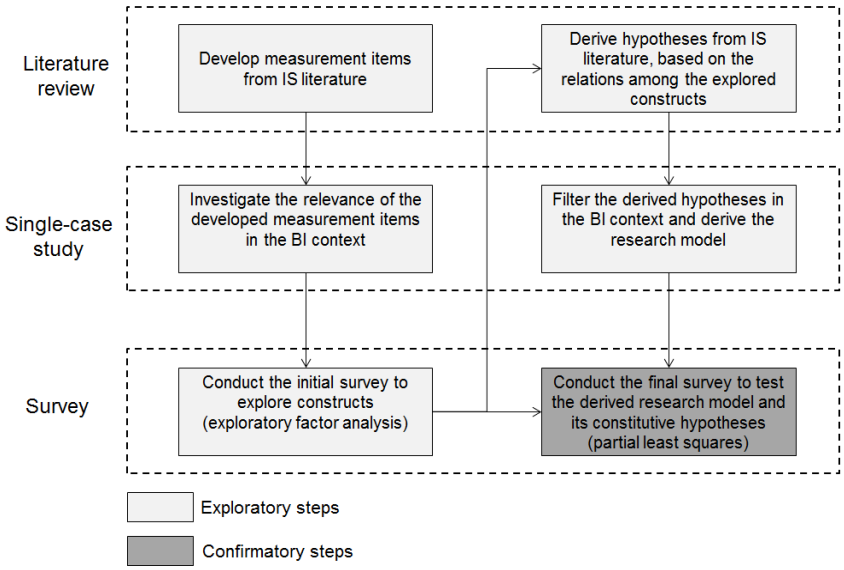

Figure 1. Research Process

3.2 Qualitative Data Collection

Following Gordon, Blake, & Shankaranarayanan (2013) who see great potential in case-based research in the area of analytical IS, we used a qualitative approach and studied a single-case in detail to collect insights from a practical perspective and to build our research model (Dyer & Wilkins, 1991). Case studies are well suited for studying BI systems because they allow one to investigate their implications as a contemporary phenomenon in their real-life context (Yin, 2003, p. 13). As such, we could investigate the relevance of the explored items and filter and hypothesize the interactions among influencing factors in the BI context based on real-world data from managers concerned with the use behavior of the potential BI users.

We conducted the case study at a globally operating financial services provider designated here as FISP (financial services provider). We selected FISP since (1) BI systems are intensely used and applied in the financial services industry (Chaudhuri, Dayal, & Narasayya, 2011) and (2) FISP is one of the pioneers in the respective industry in using BI applications. Because our study focuses on the continuous use of BI systems (instead of first-time use), the long history of using BI systems at FISP provided a grounded basis to investigate the influencing factors and their interactions.

We carried out the case study in different steps (see Figure 1) that lasted from October 2011 until July 2013. We collected primary data via semi-structured interviews with several key informants. The informants (see Table 1) regularly participated in interview sessions and provided insights from a technology perspective and from the business users' perspective. The first three informants (HGA, HCC, and BSM) represented the interface between the technical BI unit and the business users who request BI services. These informants were responsible for delivering customized BI services and, therefore, had detailed knowledge about the business user organization. The last two informants (SH-BI and BI-PM) represented the technical BI unit, which developed and maintained the technical BI infrastructure (e.g., data warehouses). The interview sessions were held on a regular basis (one day per week with one of the authors and once a month with two other authors), which provided in-depth knowledge about the organization and the interconnection and communication processes among the different organizational units that were involved in developing and operating the organization's BI landscape. We used the initial research model for structuring and transcribing the interviews and discussed each of the hypotheses and each construct regarding their match with the informants' perception of the situation at FISP and the informants' general practical experience. We also analyzed data based on the research model and its constitutive hypotheses.

Table 1. Participating Informants of FISP

#	Position	Task description	Years of BI experience	Years with FISP
1	Head of group analytics unit (HGA)	Manage internal BI key account (interface between BI business users and technical BI unit), lead organization-wide BI Competence Center	12	2
2	Head of competence center BI services (HCC)	Setup and manage BI strategy and governance related projects	13	22
3	BI business solution manager (BSM)	Define BI-based solutions for business requirements	10	10
4	Section head BI systems (SH-BI)	Provide technical infrastructure services for BI systems	2	16
5	Senior BI project manager (BI-PM)	Coordinate enhancement projects and change requests in the technical BI environment	12	12

3.3 Quantitative Data Collection

To collect input data for our statistical analysis, we designed a questionnaire based on a measurement model comprising indicator variables (IV) for each construct represented by a latent variable (LV). Table A1 in Appendix A lists the initial items, which represent the IVs in our study, including the literature that informed the explorative item collection. Our measurement model for empirically testing our hypotheses comprises a total of 43 IVs, out of which 40 IVs remained in the final model. We removed three IVs during reliability tests of the measurement model based on the actual quantitative data. We developed and refined both the measurement model and the research model based on the literature review and single-case study. We collected quantitative data in two rounds (see Figure 1). While, in the first round, we explored LVs through an exploratory factor analysis (EFA), in the second round, we tested the outlined relations among LVs. Since these two rounds of surveys are in line with each other, we incorporated relevant and valid data from the first round into the second one.

The designed questionnaire comprises three sections. In the first section, we asked for descriptive demographic information and background information regarding the participants' experience in the area of BI systems. The second part encompasses questions about each of the IVs measuring a LV that we expected to impact the continuous use of BI systems. In the third section, we asked questions about four IVs that measure continuous use of BI systems. To address typical measurement errors and additional biases, we incorporated countermeasures during the questionnaire design (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Table 2 lists and describes these measures..

For each statement in the questionnaire related to an IV, we asked the respondents to evaluate their organization on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). We formulated all

statements to measure the respondents' opinions and perceptions of the BI system and how the BI system was embedded in the organization.

Table 2. Countermeasures for Measurement Biases

Potential cause of bias	Countermeasure applied to our research
Item complexity and ambiguity, negatively worded (reverse-coded) items	We intentionally kept the item descriptions simple to make the questionnaire easy to understand. Additionally, we kept the number of reverse-coded items to a minimum to make sure that the respondents were not confused by positive/negative wording changes. During the questionnaire design, two additional researchers cross-reviewed the item descriptions for understandability, specificity, and clearness. We adapted the descriptions based on the reviewers' feedback.
Context-induced mood	We mixed semantically similar items to maintain a constant context change in the questionnaire. Therefore, the respondents did not focus on a specific context while answering the questions. Thus, it is less likely that they answered related questions identically on purpose or built context-induced mood.
Consistency motif, social desirability	To encourage the respondents to answer honestly and to the best of their knowledge, we highlighted that we evaluated all answers anonymously.

We distributed the questionnaire at four BI practitioner events in Switzerland and Germany between November 2012 and November 2013. As the participants were from German-speaking countries (i.e., Austria, Germany, Liechtenstein, and Switzerland), we conducted the survey in German. We collected 138 completed questionnaires, resulting in an average return rate of 80 percent. Table 3 presents detailed information regarding the number of responses and the return rate for each of the four events. Based on the events' list of participants, only one respondent attended more than one event. Assuming that he completed a questionnaire on the first event and knowing about his participation before the second event, we discarded his second questionnaire while collecting the responses. Therefore, each respondent is included in the analysis only once. Due to a significant number of missing values, we discarded five questionnaires. Therefore, 132 datasets remained in the sample. With focusing on responses from experienced BI users and (internal/external) suppliers, we only received contributions from experienced practitioners. Through distributing the questionnaire on BI practitioner events, we made sure that all responses were completed with deep practical insight that is necessary to achieve our research goal.

Table 3. Details of Quantitative Data Collection

Time	Event description	Location	# Responses	Return rate
Nov 2012	Large BI practitioner event taking place three times per year with changing topics (focus on BI once per year)	Switzerland	68	82%
Nov 2012	Major BI practitioner event taking place annually with about 50-60 speakers	Switzerland	16	67%
Jan 2013	BI specialist workshop	Germany	10	59%
Nov 2013	Major BI practitioner event taking place annually with about 50-60 speakers	Switzerland	44	91%
		Total	**138**	**80%**

The respondents either worked for companies using BI systems (53%) or BI vendors (47%). In order to make sure that all responses were focused on actual continuous use of BI systems, we asked the vendor representatives to answer all questions from the perspective of a customer project that they were familiar with. As a result, 28 percent of the surveys were completed from the perspective of a business unit and 72 percent from the perspective of an IT business unit. The participants worked at variously sized organizations: 16 percent worked at a small organization (up to 250 employees), 21 percent at a medium-sized one (251-1000 employees), 22 percent at a large one (1001-5000 employees), and 41 percent at a very large one (5001 employees or more). More than 85 percent of the organizations had a long lasting experience with BI systems of more than three years and a significant share of more than 38 percent had been using a BI system for six years or more. The participants completed the questionnaires from the perspective of various industries: 22 percent belonged to the financial industry, 15 percent to the

insurance industry, 14 percent to the information and communication technology (ICT) industry, 14 percent to manufacturing, 9 percent to public services, and the remaining to other industries.

Finally, to analyze quantitative data and testing our hypotheses, we followed a PLS approach to SEM. We chose a PLS approach over covariance-based approaches to SEM such as LISREL or AMOS primarily because PLS has only soft distributional assumptions, has modest sample size requirements (Chin 2010), and because it is suitable for rather complex SEMs with a high number of constructs (Urbach & Ahlemann, 2010).

4 Building the Research Model

The research model comprises the explored constructs and their interactions. We derived the research model based on the initial survey, literature review, and single-case study (see Figure 1). We explored the research constructs at the outset through executing exploratory factor analysis (EFA) on the collected quantitative data (Bischoff et al., 2014). This endeavor resulted in ten constructs (or LVs); namely, continuous use (CU), coverage of user requirements (CUR), governance (GOV), influence of the organization (IO), influence of peers (IP), information quality (IQ), perceived ease of use (PEoU), perceived usefulness (PU), trust (TRU), and user support (US) (see Table 4).

Table 4. Construct Definitions

Construct	Definition
Continuous use (CU)	The construct reflects the users' behavior regarding using the BI system intensely over a longer period of time for their day-to-day tasks.
Coverage of user requirements (CUR)	The construct reflects how well the users' requirements are addressed by the BI system and how intensely the users participate in the development process.
Governance (GOV)	The construct reflects the existence of specific governance processes for developing and operating the BI system and the degree to which the governance processes are followed and enforced.
Influence of the organization (IO)	The construct reflects the level of influence that the organization and the management have on the use of the BI system.
Influence of peers (IP)	The construct reflects the level of influence that peers have on the users of the BI system.
Information quality (IQ)	The construct reflects the information quality of the BI system. It addresses aspects of data accuracy, data consistency, currency, and timeliness.
Perceived ease of use (PEoU)	The construct reflects the users' perception of how easy it is to work with the BI system and to access its functionality.
Perceived usefulness (PU)	The construct reflects the users' perception of how the BI system contributes to their daily work and task fulfillment.
Trust (TRU)	The construct reflects the overall trust the users have in the BI system in general and the information provided by the BI system in particular.
User support (US)	The construct reflects how well the users are equipped with knowledge and resources that are necessary to use the BI system and how well they are supported in case of any system error or use problem.

We subsequently conducted a literature review on the extant IS continuous use literature to identify the interactions between the explored constructs. We finally investigated the relevance of the constructs and their relations in the BI context through a case study. The abovementioned three steps led to our deriving the research model and its constitutive hypotheses (see Figure 2). In the remainder of this section, we overview the case company and motivate each hypothesis we derived based on the existing literature and evidence in the case study.

4.1 Case Overview

FISP is a global financial services company that provides investment banking, asset management, and wealth management services for private and corporate clients worldwide. In 2014, this company operated in 50 countries with about 60,000 employees and reported USD$70 billion in revenue.

FISP's overall BI landscape was complex and various BI systems were operated focusing on different regions and business units. The studied BI unit had a regional focus on one country. It comprised approximately 200 full-time equivalent employees who were developing and maintaining the BI system from sourcing data to collecting user requirements and creating reports. In total, the studied BI unit provided reports and other analytical services for approximately 30,000 users in various business units with heterogeneous information requirements and use behavior. Based on the organizational and technical setting, the studied BI unit faced several challenges. The growing amount of data in source systems created a significant increase of historical data in the data warehouse and the data marts, which was the cause for performance issues that arose while executing complex queries in standard and ad-hoc reports and caused user complaints since the response time did not meet their expectations. Sometimes, queries were aborted due to exceeding the threshold for completion. Another challenge that FISP faced was the growing complexity of individual user requirements. User requirements were getting increasingly heterogeneous and needed to be addressed in order to establish and maintain a high level of user satisfaction. FISP addressed both challenges in order to improve the users' experience and continuous use behavior with the system from an organizational and a technical perspective.

4.2 Perceived Usefulness and Perceived Ease of Use

The existing literature on IS continuous extensively focuses on both perceived usefulness (Agarwal & Karahanna, 2000; Barnes, 2011; Bhattacherjee, 2001; Gefen, Karahanna, & Straub, 2003; Hoehle, Huff, & Goode, 2012; Kim, 2012; Limayem, Cheung, & Chan, 2003; Limayem & Cheung, 2008; Limayem et al., 2007; Premkumar & Bhattacherjee, 2008; Wang, Xu, & Chan, 2008) and perceived ease of use (Agarwal & Karahanna, 2000; Gefen et al., 2003; Tulu, Burkhard, & Horan, 2006; Wang et al., 2008). These constructs have been investigated in different contexts such as online banking systems (Bhattacherjee, 2001), business-to-consumer websites (Gefen et al., 2003), Facebook (Wang et al., 2008), and mobile data applications (Kim, 2012),

Regarding the continuous use of BI systems, the influence of these two constructs was evident at FISP. In effect, beyond the actual functionality of the system (i.e., the users' perception of the BI system's usefulness to their daily work), a user-friendly and usable system was of key interest at FISP because it directly affected the users' interaction with the system. The users should like to work with the system based on its look and feel. The organization was addressing these issues with a BI self-service initiative. The company aimed to implement a system that could be configured by each user to fit their individual needs. A proof of concept had been initiated with the help of external consultants that had proper experience with self-service initiatives. To ensure the ease of use of the existing landscape, a central unit provided general advice on how user interfaces should be designed that are ergonomic and appealing to the user. This unit also provided reviews on the ease of use of existing user interfaces, which is important since FISP expected that users with very heterogeneous skillsets, affinity to technology, and use desires work with the system equivalently.

H1: A high level of perceived usefulness of a BI system regarding the users' task fulfillment is associated with a high level of continuous use of the BI system.

H2: A high level of perceived ease of use of a BI system is associated with a high level of continuous use of the BI system.

Besides the influence of these two constructs on continues use, the existing literature has also highlighted the influence of the perceived ease of use on the perceived usefulness (Davis, Bagozzi, & Warshaw, 1989; Gefen et al., 2003; Taylor & Todd, 1995b; Thong et al., 2006; Wixom & Todd, 2005). While Gefen et al. (2003) and Thong et al. (2006) confirm this relationship based on studying business-to-consumer websites and mobile Internet services, Wixom and Todd (2005) affirm this relationship in studying the use intention of data warehouse systems.

H3: A high level of perceived ease of use of a BI system is associated with a high level of perceived usefulness of the BI system regarding the users' task fulfillment.

4.3 Influence of the Organization

The exploratory factor analysis revealed the "influence of the organization" construct as a potential factor influencing the continuous use of BI systems. This factor is related to the influence that management has on the use behavior and the existing organizational support for using the BI system. Management-related

and organizational influence factors can occur in different forms (Ragu-Nathan, Apigian, Ragu-Nathan, & Tu, 2004). On the one hand, the management can be rather supportive. Examples include an organizational setting and management decisions that lower use obstacles such as difficulties to access the BI system or advertise the system use as a top management recommendation. On the other hand, management or organizational influence can be implemented in the form of pressure to use the BI system and use policies that are enforced and regularly checked for compliance. At FISP, management measures were implemented that tie use behavior to users' personal goals. The goals were monitored based on data quality indicators and based on the amount of realized sales opportunities that were identified in reports addressing the customers' current portfolio. Additionally, the BI organization fostered system use via dedicated BI marketing initiatives, which were operationalized through information letters, roadshows, and workshops introducing new functions and features, results of current projects, and innovative initiatives and prototypes. The BI organization's goal at FISP was to analyze the potential of new technology trends (e.g., analysis of unstructured data, in-memory technology) and their proof-of-concept projects to test the feasibility of such concepts in FISP's landscape. Consequently, FISP's BI unit took the role of a technology leader through early analyses of new technologies and concepts.

H4: A high level of influence of the organization on the use of a BI system is associated with a high level of continuous use of BI systems.

Bhattacherjee et al.'s (2008) seminal study reflects the influence of the organization construct as the "facilitating conditions" construct and proves its influence on IS continuous use. Other studies discuss this relation on a more generic level. Thompson, Higgins, and Howell (1991) and Venkatesh et al. (2003) subsume related aspects in the generic construct of "social factors" and do not make further distinctions. The case data and our exploratory factor analysis show that, in the area of BI systems, we need to explicitly distinguish the overall influence of the organization and social influence of peers (see H10 in Section 4.6 below).

4.4 Coverage of User Requirements and User Support

The exploratory factor analysis also uncovered two factors; namely, "coverage of user requirements" and "user support". Semantically, both factors cover aspects related to how the user is included in the system development and operation. In effect, they focus on how the users' requirements are incorporated in the system during system development and how the user is involved and supported during system operation.

Bhattacherjee et al. (2008) reflects these constructs as "disconfirmation" (for coverage of user requirements) and "facilitating conditions" (for user support) constructs. The existing literature has also discussed the influence of user support and coverage of user requirements on perceived ease of use of BI systems (Barki & Hartwick, 1994; Chen, Soliman, Mao, & Frolick, 2000; Davis et al., 1989; Dishaw & Strong, 1999; Goodhue, 1995; Hong, Thong, & Wai-Man Wong, 2002). In the BI context, the BI unit at FISP primarily had the task to keep the system running. Without a business users' request, no fundamental system changes that affect end users were initiated. Any initiative that changes or improves the BI system's functionality and ease of use was always triggered by an end user requirement. Only the involvement of end users in the development process led to an improvement of the system's ease of use because developers themselves often did not know in which specific settings the business users used the BI system and, thus, were not able to design it according to the users' preferences without their input. In the development process, this was assured with end users' regular feedback and participation. At FISP, monthly meetings were held with representatives of business users and BI managers to discuss the current activities that had an impact on business users and elaborate on the users' current level of satisfaction with the system's ease of use.

The existing literature also sheds light on the influence of user support and coverage of user requirements on users' trust to the given information system (Aberg & Shahmehri, 2001; Ruppel & Harrington, 2000). At FISP, the regular communication of system performance and maintenance intervals and high-quality user support increased the level of trust users had in the system because they could directly influence the system design and its content. The BI unit of FISP consciously involved users in BI systems development and maintenance not only to incorporate their requirements in the system development and support their usage of the system but also to gain the users' trust to the BI system and, consequently, guarantee the return of investment on these systems.

H5: A high level of coverage of user requirements in a BI system is associated with a high level of users' trust in the BI system.

H6: A high level of user support is associated with a high level of users' trust in a BI system.

H7: A high level of coverage of user requirements in a BI system is associated with a high level of perceived ease of use of the BI system.

H8: A high level of user support is associated with a high level of perceived ease of use of a BI system.

4.5 Trust

"Trust is a complex social phenomenon that reflects technological, behavioral, social, psychological as well as organizational aspects of interactions among human and non-human agents" (Lu, Yu, Liu, & Yao, 2003, p. 216). Trust has been studied intensely in various fields whereas some focus on the trust among human agents and some focus on trust in relations between human and non-human agents. Based on its nature, IS research investigates people, task, and technology-related aspects of trust (Cody-Allen & Kishore, 2006; Gefen et al., 2003; McKnight, Choudhury, & Kacmar, 2002; Pavlou, 2003; Riedl, Hubert, & Kenning, 2010; Zhang, 2005). In a trust relationship, an IT artifact can take a mediator role (between two human agents) or take the role of the trustee (Söllner, Hoffmann, Hoffmann, Wacker, & Leimeister, 2012). IS-related research addresses both human- and non-human-related (mediator and trustee) aspects. In addition, research in the area of psychology mainly focuses on the interpersonal (human-related) aspects of trust (Mikulincer, 1998; Rempel, Holmes, & Zanna, 1985; Simpson, 2007). In our study, the BI system represents the trustee.

At FISP, use cases of BI systems and their associated reports were heterogeneous and complex. Typical use cases included customer risk ratings, market analyses and forecasts, financial management support, performance management of client advisors, and fraud prevention. Corresponding reports were based on complex algorithms and data manipulations and were consequently difficult to check on correctness beyond mere plausibility checks. Therefore, the users' only choice was to establish trust or mistrust in the system and, consequently, rely on the presented data or ignore it. Only if users trust the reports that they receive from the system and assume they are correct will they perceive the system as being useful and valuable for their daily work. The relationship between trust and perceived usefulness has already been studied intensively in other IS contexts. Gefen et al. (2003) argue that, in the area of online shopping, the systems' perceived usefulness for users' daily work is influenced by the users' trust in the respective e-vendor behind an online shopping system. Wang and Benbasat (2005) lift the trust relationship from a "human-to-human" perspective (i.e., IS having a mediator role) to a "human-to-technology (IS)" (i.e., IS as the trustee) perspective. Our case material is also in line with Hoehle et al. (2012) who discuss the importance of trust in the area of online banking. Additionally, He, Fang, and Wei (2009) have investigated this relationship and confirm the importance of trust in a knowledge management (KM) system on users' perceived usefulness of the KM system. In the area of KM, the mostly anonymous user community is responsible for adding valuable knowledge to the system that can be accessed by other users. This situation is similar to BI systems: anonymous BI staff handle the information displayed in reports and the data extraction, transformation, and load (ETL) processes.

H9: A high level of users' trust in a BI system is associated with a high level of perceived usefulness of the BI system regarding the users' task fulfillment.

4.6 Influence of Peers

According to interviewees, new BI users at FISP were often biased by their colleagues in their perception of the BI systems. Peers significantly impact the level of trust users have in a system. Different communities have already identified antecedents of the trust construct. From a psychological perspective, Mayer, Davis, and Schoorman (1995) summarize the antecedents of organizational trust, which they review in their later study (Schoorman, Mayer, & Davis, 2007). Trust plays a major role in any kind of relationship and is heavily influenced by the opinion of peers, communication, and the social context people work in (Morgan & Hunt, 1994; Trainor, 2012). In effect, the influence of peers (i.e., other users or colleagues that are important to the users and who work in their environment) can have a direct impact on the users' feelings and beliefs toward a system, which is likely to be expressed as the willingness to rely on (i.e., trust) the system (Mayer et al., 1995). IS scholars have previously studied and confirmed the importance of peer influence on IS use in general and during the post-adoptive phase in particular (Eckhardt, Laumer, & Weitzel, 2009; Sun, 2013; Sykes, Venkatesh, & Gosain, 2009; Taylor & Todd, 1995b; Wang & Meister, 2013; Ward, Brown, & Massey, 2005). Nevertheless, these studies did not

discover the intermediary construct of trust, which we hypothesize to be one important construct for bridging the gap between peer influence and continuous use of BI systems.

H10: A high level of peers' positive influence on users is associated with a high level of users' trust in a BI system.

4.7 Information Quality

Owing to voluntary use of BI systems, trust is crucial to motivate users to continuously use the BI systems. To this end, FISP placed a specific emphasis on the quality of the provided information to actual and potential users. Information quality refers to completeness, accuracy, format, and currency of the provided information by a given system (Wixom & Todd, 2005). Since FISP had a huge number of applications that each followed its own data model and data definition, the consistency and quality of the loaded data in BI systems that are used to develop analytical reports is highly relevant. To obtain and maintain a sufficient level of information quality and make sure that users could trust the system, the studied BI unit incorporated special measures such as a "golden source" approach, detailed consistency checks, and a comprehensive sign-off procedure during the user acceptance tests. The so-called "golden source" approach ensured that data was only copied from one central and trustworthy source system into the BI system for every data category. This approach was supported by a clear definition of the "master" system for every data category. For instance, a dedicated system existed for customer data and a consolidation of customer data from different sources was not necessary on BI level. Thus, the likeliness of inconsistent data was rather low. Comprehensive consistency checks of loaded records made sure that data was imported into the BI system in the correct sequence. Improbable variations in tables and unexpected values were also identified. During the user acceptance test, key users test new or modified reports with a special focus on the correctness of the presented information. They need to verify the quality of the newly developed or changed report/analysis and check whether the quality criteria of the business unit were met.

The influence of the provided information's quality on trust in a given system that provides that information has already been discussed in the IS literature (Kim, Ferrin, & Rao, 2008; Nicolaou & McKnight, 2006; Siau & Shen, 2003). Further, the high importance of information quality on use behavior and continuous use has been hypothesized in various popular IS-related research models. Hsieh et al. (2011) discuss its importance for the continuous use of an operational customer relationship management system. Cody-Allen and Kishore (2006) discuss and hypothesize the impact of information quality on trust in relation to e-business systems but do not empirically test the relationship for this use case.

H11: A high level of information quality of a BI system is associated with a high level of users' trust in the BI system.

4.8 Governance

In order to gain users' trust in the BI systems, FISP also took advantage of a well-established and systematic governance regime. The system change process at FISP that impacted users' trust in the BI systems was transparent and users knew that changes were only made in accordance to the defined, communicated, and lived governance procedures. The aim of the existing governance regime was to make sure that system changes were executed in a controlled and traceable way and that the negative effects on the users were kept to a minimum. To be more precise, any BI system change at FISP was carefully evaluated for its impact on the overall system and only released after an intensive user test. Release cycles were carefully planned so that every week there were two opportunities for releasing small changes into the BI system. Major system changes on software and hardware level were performed at four or five change weekends per year, which were planned well in advance including adjacent public holidays to have more time for potentially necessary rollbacks. Detailed execution plans for such weekends were tested in advance in order to reduce the risk and likeliness of negative impact on the users' trust. Any change was planned and discussed during the monthly meetings of the BI governance board that comprises the major BI stakeholders from the organization's technical (i.e., representatives of the BI infrastructure unit and analytical services) and business sides (i.e., representatives of the business units and BI users). Every system change that could have an impact on the BI system users was discussed and planned during the meetings and needed to be approved by the stakeholders from business side. The governance board was also used as a feedback interface regarding user satisfaction with the BI system and provided traceability and transparency of the BI unit's actions. In addition to the

discussions of change initiatives on manager level, email newsletters were sent to every user informing them about current BI projects, change initiatives, and scheduled maintenance intervals and change weekends.

BI governance has been already discussed in the extant literature (Cheung & Lee, 2000; Glaser & Stone, 2008; Horakh, Baars, & Kemper, 2008; Watson, Fuller, & Ariyachandra, 2004; Williams & Williams, 2010), especially from a data-governance perspective. Concerning the influence of governance on users' trust, Cheung and Lee (2000) hypothesize (but do not test) the impact of the existing legal framework on the level of customers' trust in an online shopping site. Transferring this relation from a public setting into an organization, we argue that we can see governance rules and regulations as an organization's internal legal framework that exists for operating and developing a BI system.

H12: A high level of defined and enforced governance procedures for operating and developing a BI system is associated with a high level of users' trust in the BI system.

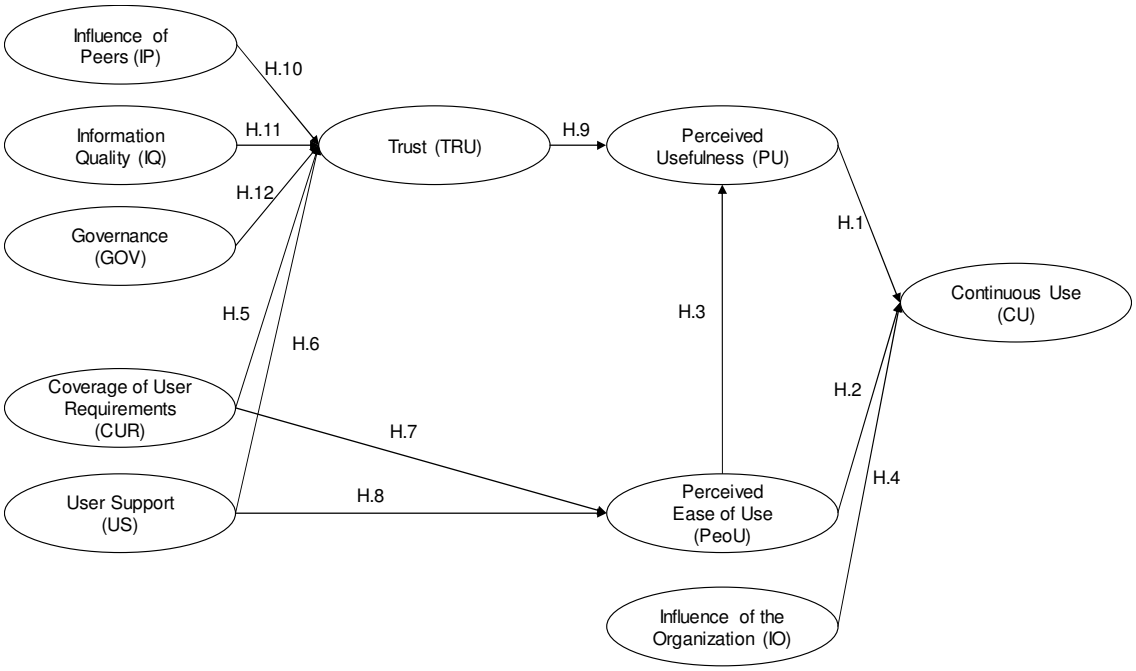

Figure 2. Research Model

5 Results of Quantitative Data Analysis

We measured all constructs in a reflective mode. To assess the quality of our outer and inner model, we followed the approach that Götz, Liehr-Gobbers, and Krafft (2010) suggest and evaluated the measurement model in terms of (1) content validity, (2) indicator reliability, (3) construct reliability, (4) convergent validity, and (5) discriminant validity. To assess the quality of our measurement model, we used the t-statistics approach and applied bootstrapping with 5000 re-samples of the original sample size (Hair, Hult, Ringle, & Sarstedt, 2014). Additionally, we evaluated the structural model based on the determination coefficient (R^2) of each dependent LV, the path coefficients between the LVs including their significance, and the model's predictive validity. We first executed our analysis with the whole set of indicators. During the quality test of the model, we removed three IVs: CUR.1, PEoU.8, and US.1 (see Table B1 in Appendix B) to improve the overall quality of the model, especially the determination and path coefficients including their level of significance.

To assure content validity, we built our model and its constitutive hypotheses on scientifically accepted measurement instruments in the existing IS literature and on a practical case in the BI context. To evaluate the indicator reliability, which "specifies which part of an indicator's variance can be explained by the underlying latent variable" (Götz et al., 2010, p. 694), one needs to look more closely at the factor loadings. Researchers recommend that the loadings should be higher than 0.7 (Götz et al., 2010) but loadings higher than 0.4 can be accepted in the model; any factor with a loading below 0.4 should be

removed from the model (Hulland, 1999). Therefore, the final model only contained indicators with a factor loading between 0.624 and 0.949 and only five IVs with a loading below 0.7 (see Table B1 in Appendix B).

Construct reliability specifies that all IVs measure the same construct. To determine a construct's reliability, we applied the measures composite reliability (CR) and Cronbach's alpha (Cronbach, 1951). For CR and Cronbach's alpha, the recommended lower limit is 0.7 (Gefen, Straub, & Boudreau, 2000; Nunnally & Bernstein, 1994). In our model, the values of both CR and Cronbach's alpha exceeded the suggested thresholds (see Table C1 in Appendix C) so that the IVs for all constructs measure the constructs adequately. To determine the model's convergent validity, the average variance extracted (AVE) should be higher than 0.5 (Bagozzi & Yi, 1988), which is the case for all constructs in our model (see Table C1 in Appendix C). Discriminant validity describes the degree to which the IVs of different LVs are related to each other. One can assess it by comparing the LVs' AVE to the squared correlations between constructs (Götz et al., 2010). Discriminant validity is shown when the LVs' AVEs are significantly larger than any squared correlation between the given LV and the other LVs. Table D1 in Appendix D shows the results of this test. The AVE value for each LV is significantly larger than the corresponding squared inter-construct correlation.

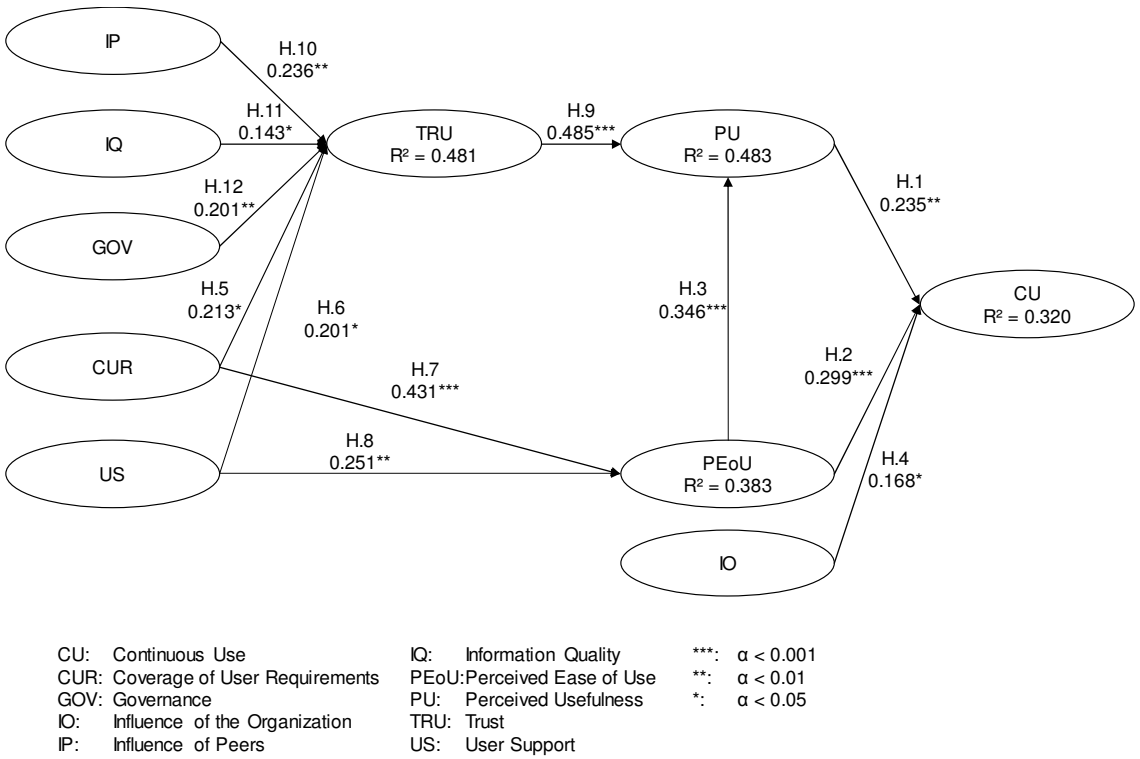

Figure 3. PLS Analysis of the Research Model

Figure 3 illustrates the evaluation of the structural model and Table 5 summarizes it. The structural model is represented by all LVs and the corresponding hypotheses that describe the relationships between the LVs. The evaluation shows that all hypotheses regarding the continuous use of BI systems were supported. As Figure 3 illustrates, our overall model explains 32.0 percent of the variance of the continuous use LV. The first quality criterion that we evaluated was the determination coefficient (R^2) of each endogenous LV. R^2 specifies the percentage of the endogenous variables' explained variance. No threshold exists that can be used for determining the acceptability of the determination coefficient. Whether the values of R^2 are acceptable or not depends on the individual study (Götz et al., 2010). In our model, 32.0 percent of the variance of continuous use (CU) was jointly explained by PU, PEoU, and the level of IO. This value confirms the significant explanatory power of our model. The variance of PU, in turn, was explained at a level of 48.3 percent by PEoU and TRU. The other values for the determination coefficient were 48.1 percent for TRU (jointly explained by IP, IQ, GOV, CUR, and US) and 38.3 percent for PEoU (explained by CUR and US).

All but two hypotheses (H4 and H11) of the significant path coefficients of our model were larger than the recommended threshold of 0.2 (Chin, 1998). To test the statistical significance of the hypotheses, we used

p-value (α). We found all hypotheses to be statistically significant at least the 0.05 level. Except for four hypotheses (H4, H5, H6, and H11), the others were also significant at the 0.01 level (H1, H8, H10, and H12) and even at the 0.001 level (H2, H3, H7, and H9) (see Table 5).

We finally assessed our model's predictive validity by means of a non-parametric Stone-Geisser test. We applied the blindfolding procedure implemented in SmartPLS by using an omission distance of 7. The procedure assumes that parts of the empirical dataset is missing and then tries to reconstruct the "missing" data using the model and the PLS parameters (Götz et al., 2010). Predictive validity is given if the Stone-Geisser criterion is larger than 0. This holds true for our model; thus, we achieved predictive validity.

Table 5. Summary of Testing Hypotheses

#	Hypothesis	Path coefficients	Support by p-value (α)
H1	PU → CU	0.235	Yes (α < 0.01)
H2	PEoU → CU	0.299	Yes (α < 0.001)
H3	PEoU → PU	0.346	Yes (α < 0.001)
H4	IO → CU	0.168 (weak relationship)	Yes (α < 0.05)
H5	CUR → TRU	0.213	Yes (α < 0.05)
H6	US → TRU	0.201	Yes (α < 0.05)
H7	CUR → PEoU	0.431	Yes (α < 0.001)
H8	US → PEoU	0.251	Yes (α < 0.01)
H9	TRU → PU	0.485	Yes (α < 0.001)
H10	IP → TRU	0.236	Yes (α < 0.01)
H11	IQ → TRU	0.143 (weak relationship)	Yes (α < 0.05)
H12	GOV → TRU	0.201	Yes (α < 0.01)

6 Discussion and Conclusion

6.1 Research Contributions and Implications

The existing literature has long focused on the continuous use of information systems. Besides general theories (e.g., Ahuja & Thatcher, 2005; Bhattacherjee, 2001; Bhattacherjee et al., 2008; Jasperson et al., 2005; Kim et al., 2007; Limayem et al., 2007; Saeed & Abdinnour-Helm, 2008; Thong et al., 2006; Venkatesh et al., 2011), continuous use has been studied in specific contexts such as social virtual worlds (Mäntymäki & Riemer, 2012), electronic medical records (Mettler, 2012; Shaw & Manwani, 2011), the World Wide Web in general (Hsu et al., 2004), and websites in particular (Lin et al., 2005). The specificities of BI systems such as voluntary use, long-term return of investments, heterogeneity of their use cases, and innovative use rather than routine use in such systems motivate our investigating continuous use in the specific context of BI systems as well. The extant literature only concentrates on partial aspects of BI systems' continuous use. As such, we lack insights about how we can theorize the continuous use of BI systems. We address this research gap in this paper by studying the factors influencing the continuous use of BI systems and their interactions.

The contribution of this study is twofold. First, this study confirms well-established constructs and relations in the specific context of BI systems, which are generally theorized for the continuous use of IS. This applies for perceived usefulness, perceived ease of use, trust, and information quality constructs. Even though the existing literature examines these constructs and their constitutive relations, our study shows the applicability of these constructs and relations in the context of BI systems with regard to their specificities. In the existing literature, scholars have studied these constructs and relations in other specific contexts such as online banking systems (Bhattacherjee, 2001; Hoehle et al., 2012), e-business systems (Cody-Allen & Kishore, 2006; Gefen et al., 2003), mobile applications (Kim, 2012; Thong et al., 2006), knowledge management systems (He et al., 2009), customer relationship management systems (Hsieh et al., 2011), and data warehouses (Nelson et al., 2005) and eventually generalized them to the overarching context of IS. In line with the aforementioned studies, our study affirms the applicability of

these constructs and relations in the BI context as well, which reinforces their generalizability in the context of various types of information systems.

For example, based on the confirmed relationship between perceived ease of use and perceived usefulness (H3), it seems clear that system design addressing ease of use has a significant effect on the users' perception of the BI system's usefulness and its value contribution to the users' daily tasks. The important implication is that, as with as other types of information systems, the look and feel of the BI system's frontend is an important design artifact in the system implementation process. Current projects in research and practice often follow the design-to-build approach (Marchand & Peppard, 2008) rather than a user-centric design-for-use method. Studies that discuss critical success factors of BI systems also merely focus on the technical, functional, and implementation-related factors (Hwang & Xu, 2008; Yeoh & Koronios, 2010). Therefore, they often do not examine user and use-related factors (Brenner et al., 2014). Our findings show that it is crucial to explicitly consider this interdependency in research and in practice. BI managers need to make sure that user-centric aspects are considered and explicitly addressed. We can observe in practice that user-centric aspects of BI solutions are barely considered in the standard project handbooks. This aspect becomes even more important when IT units not only design solutions for the average user but also consider different user types, different working styles, and actual use situations (Mayer et al., 2012), which will be necessary to also make current trends such as self-service BI or mobile BI (Stodder, 2012; Swoyer, 2012) a success. Otherwise, the issue of user centricity will become a bottleneck in exploiting the ever-growing amount of data (as in big data approaches (Jacobs, 2009)) that is nowadays available to organizations.

Our study also confirms the significant influence of the users' level of trust on the users' perception of the BI systems' usefulness for their daily tasks (H9). This finding stimulates new research opportunities for future studies on (a) continuous use of IS in general and BI systems in particular and (b) trust itself. On the one hand, future research should address the construct of trust in the BI systems to investigate the continuous use or other BI systems-related behavioral scenarios. Besides its importance for BI systems, we argue that it should also be considered as an influence factor in general models related to continuous use because ISs more and more take the role of a trustee in IS-user relationships (Söllner et al., 2012). On the other hand, through using our findings that illustrate the influencing constructs on trust along with the impact of trust, we encourage prospective research to further examine the construct of trust in IS studies.

Moreover, our study makes the first step toward confirming the influence of information quality on the well-established construct of trust (H11). In effect, the correctness of the information in BI systems cannot be verified by its users beyond mere plausibility checks. Therefore, users need to establish trust in the BI systems through trusting in the outputs of BI systems. BI systems' main purpose is to present information (Wixom & Watson, 2010). Therefore, the system's information quality is of particular interest for users and needs to be explicitly included in any model focusing on user-centric research of BI systems and also any other ISs that mainly aim to present information.

Second, this study introduces either new constructs or new relations through the given investigation in the context of BI systems. This applies for the influence of the organization, coverage of user requirements, user support, influence of peers, and governance constructs. Further studies on the continuous use of other types of information systems can use these constructs and relations and eventually theorize them as general insights to the overarching context of IS. Since these constructs and/or relations are new to the existing body of knowledge, in the remainder of this section, we focus on our findings' implications for research and practice rather than comparing the findings with existing discourses in the extant literature.

For instance, our study introduces new constructs of influence of the organization (H4), coverage of user requirements (H5 and H7), and user support (H6 and H8). Even though these constructs are latent in Bhattacherjee et al.'s (2008) "disconfirmation" and "facilitating conditions" constructs and Thompson et al.'s (1991) and Venkatesh et al.'s (2003), "social factors" construct, we explore and derive these new constructs owing to their explicit importance in the BI context. We illustrate the significant impact of influence of the organization on the BI systems' continuous use (H4). This relates to management support and organizational initiatives to foster the continuous use of BI systems. Therefore, BI managers need to consider this factor along with the overemphasized technical aspects of BI systems.

Moreover, users' requirements and needs in system development, system change, and system operation need to be continuously included in the respective processes. Including these aspects enables developers to specifically address users' actual requirements and fulfill their expectations about perceived ease of use

(H7). In addition to general recommendations regarding systems' ease of use that the ISO 9241 family describes (ergonomics of human-system interaction) or that we can adopt from other IS fields to BI systems (Jeng, 2005; Palmer, 2002; Tractinsky, Katz, & Ikar, 2000), the coverage of various users' individual preferences assures the ease of use of system for different types of users. The coverage of user requirements also fuels the ongoing discussion of redefining the division of labor among business and IT units in the BI field or the role of key users as links between business (users) and IT (developers) in a BI organization. For research, this makes existing theory such as actor network theory (Callon, 1986; Law, 1992) effective in the field of BI. In addition, trust in the system is significantly impacted by the level of the covered user requirements (H5). Users more likely trust a BI system if they have been and are continuously involved in its development in comparison to a system that has been built independently. They can influence the system's shape and functionality and, therefore, trust the system..

Similar to the coverage of user requirements, we introduce the user support construct and its influence on perceived ease of use and trust in our study (H6 and H8). In line with the provided argumentations for the coverage of the user requirements, the more users are supported in the development and usage of BI systems, the higher ease of use will be perceived and the more users will trust in the system. This finding is a clear message for BI managers that the continuous support of different types of users will bring about not only users' perceived ease of use (since users are supported continuously and their issues with the system have been considered) but also trust in the BI system (since users have been involved in the system troubleshooting and their concerns have been taken into account in the system development and maintenance).

Building on our second contribution, we introduce the new relations between influence of peers (H10) and governance (H12) with trust in the system. Even though neither the influence of peers or governance are new constructs in the IS literature (as opposed to the influence of the organization, coverage of user requirements, and user support), their influence on trust has not been studied so far. The influence of peers (i.e., colleagues that have similar or even identical tasks) significantly affects users' level of trust in the BI system (H10). Because other users already have some experience with using a system (which can either be negative, neutral, or positive), they can share their experience with colleagues and, therefore, contribute to forming their opinion and their level of trust in the BI system. As a consequence, we note for future research that this factor needs additional attention to discover measures that can help to actively manage peers' influence. For practice, training sessions for new users and involving champions and key users in introducing the BI system to new users will foster the usage and continuous use of BI systems. Further, BI units should be in continuous contact with all types of users—specifically new users— to avoid negative impressions about the system.

Moreover, the investigated relation between governance and trust (H12) highlights the importance of existing, lived (i.e., enforced), and well-communicated governance procedures in BI units and in business units that use a BI system. Even if users are not directly affected by the governance rules, they need to be informed that the rules exist for developing and operating the BI system and that the rules are strictly enforced. Therefore, rules need to be communicated to all employees that are in touch with the BI system whether they are directly affected by the rules (e.g., developers, IT employees, key users) or not (e.g., "regular" users). This relation requires additional research. Our work shows that governance procedures for BI systems development and operation need to be put in place and lived to have a positive effect on users' level of trust in the system. However, we did not specifically research the exact definition of the rules. As such, additional research could elaborate on the exact governance rules that are important for developing and operating BI systems development and evaluate the strength of the influence of each type of rule on users' level of trust in the system.

To conclude, we illustrate that our research contributes factors that BI managers striving for continuous use of their systems need to consider. Therefore, the identified factors need to be operationalized by means of specific initiatives and measures that can be implemented in practice for directly influencing the use behavior of BI systems' users. Our work contributes to both design-oriented and descriptive research. To design BI-related artifacts such as BI management methods, design principles, or specific instantiations (Hevner & Chatterjee, 2010), we provide the design researcher with factors that need to be specifically addressed to make sure that the final instantiation is continuously used. BI management methods also need to operationalize the discussed constructs that influence continuous use and make them usable in practice. For descriptive research, our work tests well-established constructs and outlines new constructs or relations that should also be considered in future research that aims to create a comprehensive understanding of continuous use or to build a general model of continuous use of IS. We

show that the mentioned constructs that have not been part of existing general continuous use literature have a significant impact on continuous use of BI systems.

6.2 Limitations

Owing to the use of both exploratory and confirmatory perspectives in a mixed-methods research, our study has certain limitations. The first limitation concerns our data sample. We collected our empirical data in a controlled setting among specialists in the field of BI. However, our data set cannot be considered representative. Second, we collected our data in German-speaking countries only. Therefore, one could argue that results are valid only in these areas. However, we do not expect significantly different results if we distributed our questionnaire to a more international target group owing to the fact that the major group of our study (very large organizations) today are influenced by diverse cultural backgrounds not only among their average employees but also in their top management. Third, from a theoretical perspective, our work does not incorporate all constructs of previous theory-based studies on continuous use because we followed a case-driven method for filtering our hypotheses (Dyer & Wilkins, 1991; Gordon et al., 2013). The inherent characteristic of this approach is that one includes only those hypotheses that are filtered by the case study and leaves aside additional constructs that can be included from a theoretical point of view (such as “satisfaction” and “continuance intention” constructs in the study of Bhattacherjee et al. (2008)). However, the advantage of a case-driven approach is that it can contribute hypotheses that are new to the selected field of research and that are inspired bottom-up by qualitative empirical data. The fourth limitation of our work is related to our single-case research design. Because we base our research model on the experience we gained from one case, we only took into account hypotheses that were observable at FISP. Therefore, we missed some other constructs or relations that could be considered if we chose another or multiple cases. This leaves the opportunity for additional research to discover and test additional hypotheses to expand our model.

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Appendix A: Survey Items and Supporting Literature

Table A1. Survey Items and Supporting Literature

IV	Survey item	Adapted from
CU.1	The users continue using the BI system only if there is no alternative solution. (inverse)	Bhattacherjee, (2001)
CU.2	The users also continue using the BI system if there are alternative solutions.	Bhattacherjee (2001)
CU.3	The users use the BI system as frequently as necessary for their tasks.	Venkatesh, Brown, Maruping, & Bala (2008)
CUR.1	The users' opinion is taken into account during the BI system development and design process.	Barki & Hartwick (1994), Chen et al. (2000), Kim & Lee (1986), Olson & Ives (1981)
CUR.2	The /BI system is compatible with other systems the users use.	Ajzen (1991), Taylor & Todd (1995a, 1995b), Venkatesh et al. (2003)
CUR.3	A specific person (or group) is available for assistance with BI system difficulties.	Thompson et al. (1991), Venkatesh et al. (2003)
CUR.4	The providers (designers and suppliers) of the BI system understand the users' specific requirements and needs.	Chen et al. (2000), DeLone & McLean (2003), Pitt, Watson, & Kavan (1995)
CUR.5	The content of the BI system is regularly adapted to the users' requirements.	Barki & Hartwick (1994), Kim & Lee (1986), Olson & Ives (1981)
GOV.1	The existing governance processes for BI system operation are enforced and followed.	Bischoff et al. (2014), Cheung & Lee (2000)
GOV.2	Governance processes for BI system development exist.	Bischoff et al. (2014), Cheung & Lee (2000)
GOV.3	The existing governance processes for BI system development are enforced and followed.	Bischoff et al. (2014), Cheung & Lee (2000)
GOV.4	Governance processes for BI system operation exist.	Bischoff et al. (2014), Cheung & Lee (2000)
IO.1	The senior management of this business has been helpful in the use of the BI system.	Thompson et al. (1991), Venkatesh et al. (2003)
IO.2	In general, the organization has supported the use of the BI system.	Thompson et al. (1991), Venkatesh et al. (2003)
IP.1	People who are important to the users think that they should use the BI system.	Ajzen (1991), Davis (1989), Fishbein & Ajzen (1975), Mathieson (1991), Taylor & Todd (1995a, 1995b), Venkatesh et al. (2003)
IP.2	People who influence the users' behavior think that they should use the BI system.	Ajzen (1991), Davis (1989), Fishbein & Ajzen (1975), Mathieson (1991), Taylor & Todd (1995a, 1995b), Venkatesh et al. (2003)
IQ.1	The information provided by the BI system is perceived to be accurate.	Chen et al. (2000), DeLone & McLean (1992)
IQ.2	The information provided by the BI system is perceived to be consistent and free from bias.	DeLone & McLean (1992)
IQ.3	The information provided by the BI system is perceived to be current and timely.	Chen et al. (2000), DeLone & McLean (1992)
PEoU.1	The users perceive learning to operate the BI system as easy.	Ajzen (1991), Davis (1989), Davis et al. (1989), Moore & Benbasat (1991), Taylor & Todd (1995a, 1995b), Venkatesh et al. (2003)

IV	Survey item	Adapted from
PEoU.2	The users perceive the BI system as easy to use.	Ajzen (1991), Davis (1989), Davis et al. (1989), Moore & Benbasat (1991), Taylor & Todd (1995a, 1995b), Venkatesh et al. (2003)
PEoU.3	The users think that it would be easy for them to become skillful at using the BI system.	Davis (1989), Davis et al. (1989), Moore & Benbasat (1991), Thompson et al. (1991), Venkatesh et al. (2003)
PEoU.4	The users perceive the access to the BI system as convenient.	DeLone & McLean (1992)
PEoU.5	The users perceive their interaction with the BI system to be clear and understandable.	Davis (1989), Davis et al. (1989), Moore & Benbasat (1991), Venkatesh et al. (2003)
PEoU.6	The users like using the BI system.	Compeau & Higgins (1995), Compeau, Higgins, & Huff (1999), Moore & Benbasat (1991), Venkatesh et al. (2003)
PEoU.7	The presentation (accuracy and currency) of the results within the BI system totally fulfills the users' expectations.	Chen et al. (2000), DeLone & McLean (1992)
PEoU.8	The users perceive the information provided by the BI system as understandable.	Chen et al. (2000), DeLone & McLean (1992)
PU.1	The users think that using the BI system would increase their productivity.	Bhattacherjee et al. (2008), Davis (1989), Davis et al. (1989), Moore & Benbasat (1991), Venkatesh et al. (2003)
PU.2	The users think that using the BI system would enable them to accomplish their tasks more quickly.	Davis (1989), Davis et al. (1989), Venkatesh et al. (2003)
PU.3	The users would find the BI system useful for their job.	Davis (1989), Davis et al. (1989), Venkatesh et al. (2003)
PU.4	The users think that using the BI system would make their job easier.	Davis (1989), Davis et al. (1989), Moore & Benbasat (1991), Venkatesh et al. (2003)
PU.5	The users perceive that using the BI system is a good idea.	Davis (1989), Fishbein & Ajzen (1975), Taylor & Todd (1995a, 1995b), Venkatesh et al. (2003)
PU.6	The users perceive the information provided by the BI system to be useful for their tasks.	Davis (1989), Davis et al. (1989), Venkatesh et al. (2003)
PU.7	The users think that the BI system makes their tasks more interesting.	Thompson et al. (1991), Venkatesh et al. (2003)
TRU.1	The users use the BI system for answering questions which are of high importance for the organization.	Gefen et al. (2003), Hoehle et al. (2012), McKnight et al. (2002), Nicolaou & McKnight (2006), Wang & Benbasat (2005)
TRU.2	The users use the BI system for answering complex questions.	Gefen et al. (2003), Hoehle et al. (2012), McKnight et al. (2002), Nicolaou & McKnight (2006), Wang & Benbasat (2005)
TRU.3	The BI system as a whole is perceived by the users to be trustworthy.	Bhattacherjee (2002), Gefen (2002), Jarvenpaa et al. (2000)
US.1	The users think that they have the knowledge necessary to use the BI system.	Ajzen (1991), Taylor & Todd (1995a, 1995b), Venkatesh et al. (2003)
US.2	The users think that they have the resources necessary to use the BI system.	Ajzen (1991), Bhattacherjee et al. (2008), Taylor & Todd (1995a, 1995b)
US.3	The users perceive the BI system helpdesk's operating hours as convenient.	Chen et al. (2000), Pitt et al. (1995)
US.4	The BI system's service level is perceived to be high.	Pitt et al. (1995)
US.5	The BI system is perceived to be reliable.	DeLone & McLean (1992)

Appendix B: PLS SEM Results per Item

Table B1. PLS SEM Results per Item

IV	Mean	SD	Loading before items were dropped	Loading after items were dropped	t-statistics
CU.1	2.27	1.025	0.666	0.667	8.873
CU.2	3.57	0.861	0.821	0.821	21.869
CU.3	4.12	0.891	0.864	0.864	26.503
CUR.1	3.4	0.978	0.668	Dropped	Dropped
CUR.2	3.43	0.922	0.7	0.73	13.02
CUR.3	3.72	0.948	0.74	0.75	13.044
CUR.4	3.42	0.916	0.764	0.784	15.68
CUR.5	3.3	0.85	0.653	0.661	10.799
GOV.1	3.27	1.062	0.913	0.913	42.882
GOV.2	3.32	1.103	0.945	0.945	62.074
GOV.3	3.22	1.011	0.922	0.922	60.274
GOV.4	3.38	1.166	0.884	0.884	33.869
IO.1	3.52	1.047	0.837	0.837	12.545
IO.2	3.38	0.972	0.949	0.949	50.793
IP.1	3.7	0.851	0.923	0.923	34.77
IP.2	3.69	0.891	0.931	0.931	56.84
IQ.1	3.66	0.845	0.906	0.906	49.818
IQ.2	3.34	0.853	0.802	0.802	14.316
IQ.3	3.77	0.904	0.786	0.786	14.379
PEoU.1	3.35	0.867	0.767	0.784	18.644
PEoU.2	3.36	0.868	0.85	0.86	34.675
PEoU.3	3.21	0.869	0.793	0.814	23.78
PEoU.4	3.09	0.869	0.823	0.829	28.692
PEoU.5	3.25	0.755	0.811	0.827	25.186
PEoU.6	3.14	0.842	0.69	0.688	12.189
PEoU.7	3.18	0.796	0.679	0.668	11.221
PEoU.8	3.43	0.772	0.626	Dropped	Dropped
PU.1	3.74	0.911	0.814	0.815	21.585
PU.2	3.82	0.995	0.876	0.877	34.796
PU.3	3.83	0.863	0.758	0.758	14.96
PU.4	3.72	0.885	0.758	0.758	16.745
PU.5	3.7	0.861	0.798	0.799	17.763
PU.6	3.77	0.757	0.722	0.719	12.856
PU.7	3.23	0.852	0.624	0.624	12.24
TRU.1	3.67	0.936	0.883	0.882	37.056
TRU.2	3.49	0.968	0.86	0.859	32.132
TRU.3	3.68	0.772	0.76	0.761	14.992
US.1	3.32	0.803	0.621	Dropped	Dropped
US.2	3.4	0.895	0.783	0.766	17.03
US.3	3.49	0.866	0.733	0.749	14.759
US.4	3.54	0.735	0.795	0.809	20.897
US.5	3.67	0.845	0.687	0.736	14.33
US.3	3.49	0.866	0.733	0.749	14.759

Appendix C: PLS SEM Quality Criteria Overview

Table C1. PLS SEM Quality Criteria Overview

	AVE	CR	R^2	Cronbach's Alpha
CU	0.622	0.83	0.32	0.694
CUR	0.537	0.822		0.711
GOV	0.839	0.954		0.937
IO	0.801	0.889		0.767
IP	0.86	0.924		0.837
IQ	0.694	0.871		0.78
PEoU	0.616	0.918	0.383	0.894
PU	0.589	0.909	0.483	0.881
TRU	0.698	0.874	0.481	0.781
US	0.586	0.85		0.764

Appendix D: Correlation Matrix

Values on the main diagonal show the AVE. The values below the main diagonal represent the squared inter-factor correlations.

Table D1. Correlation Matrix

	CU	CUR	GOV	IO	IP	IQ	PEoU	PU	TRU	US
CU	**0.622**									
CUR	0.190	**0.537**								
GOV	0.072	0.066	**0.839**							
IO	0.147	0.199	0.076	**0.801**						
IP	0.019	0.118	0.022	0.151	**0.860**					
IQ	0.137	0.236	0.076	0.148	0.070	**0.694**				
PEoU	0.232	0.344	0.009	0.121	0.069	0.153	**0.616**			
PU	0.224	0.283	0.035	0.222	0.243	0.180	0.282	**0.589**		
TRU	0.175	0.290	0.152	0.247	0.201	0.236	0.145	0.381	**0.698**	
US	0.237	0.383	0.090	0.220	0.128	0.370	0.268	0.324	0.318	**0.586**

About the Authors

Stefan Bischoff used to work as a research assistant at the Institute of Information Management, University of St. Gallen, Switzerland. He received his PhD from the University of St. Gallen and holds a master's degree in information systems from Murray State University and a Master of Science with Honors degree from the University of Regensburg. His research mainly focuses on use-, user-, and utility-centric aspects of business intelligence systems, executive information systems and enterprise architecture. His work has been published in *MIS Quarterly Executive* and in international conferences.

Stephan Aier is an assistant professor of information management at the University of St. Gallen, Switzerland. He received a Doctorate and a Master's degree from the Technical University of Berlin, Germany. He is engaged in applied research with industry partners as well as in foundational research projects investigating enterprise-wide IS phenomena such as business intelligence, enterprise architecture, and enterprise transformation. His work has been published in journals such as *Business and Information Systems Engineering* and *Information Systems and e-Business Management* and in conferences such as International Conference on Information Systems and European Conference on Information Systems.

Mohammad Kazem Haki is a postdoctoral researcher at the Institute of Information Management, University of St. Gallen (HSG), Switzerland. He holds a Doctorate's degree in information systems from the HEC Lausanne, Switzerland as well as a Bachelor's degree in business administration and Master's degree in IT management from the University of Tehran, Iran. His research focuses mainly on the architectural thinking and IS architecture in multinational corporations. His work has been published in journals such as *Information Systems and Change Management* and *Advances in Information Sciences and Service Sciences* and in conference proceedings such as International Conference on Information Systems and European Conference on Information Systems.

Robert Winter is tenured chair of business & information systems engineering at University of St. Gallen (HSG), director of HSG's Institute of Information Management, founding academic director of HSG's Executive Master of Business Engineering program and academic director of HSG's PhD in Management program. He received Master's degrees in business administration and business education as well as a Doctorate in social sciences from Goethe University, Frankfurt, Germany. His research areas include situational method engineering, enterprise architecture management, transformation management, healthcare management and management of very large IT projects.

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