E-Business Adoption at the Firm Level: Comparing the Predictive Power of Competing IS Adoption Models

Completed Research Paper

Simon Thanh-Nam Trang
University of Göttingen
Chair of Information Management
Platz der Göttinger Sieben 5
37073 Göttingen
strang@uni-goettingen.de

Sebastian Zander
University of Göttingen
Chair of Information Management
Platz der Göttinger Sieben 5
37073 Göttingen
szander1@uni-goettingen.de

Lutz M. Kolbe
University of Göttingen
Chair of Information Management
Platz der Göttinger Sieben 5
37073 Göttingen
lkolbe@uni-goettingen.de

Abstract

E-business adoption research at the firm level has a strong grounding in both prior and current IS research. When designing empirical studies, researchers choose among a variety of base adoption models. This study is the first to empirically compare three prominent models regarding their explanatory power: the technology-organization-environment model, the task-technology-fit model, and the unified theory of acceptance and use of technology. Therefore, a within-subject study was conducted using data gathered from 204 firms in the German wood industry. The results demonstrate that each model can contribute in its own way to the understanding of different stages. Surprisingly, the most parsimonious model in terms of explanatory variables was revealed to have a constant and comparably high degree of explanatory power at all stages of e-business adoption. The results provide insights into the explanatory power of base models and can serve as guidance for the base model choices of future studies.

Keywords: E-business adoption, competing theories, technology-organization-environment model, task-technology-fit model, unified theory of acceptance and use of technology
Introduction

Research on technology adoption in general and technology adoption at the firm level in particular has a long tradition in the information systems (IS) discipline and is often regarded as one of the most mature streams (Brown et al. 2010; Venkatesh et al. 2003). As the potentials of e-business use are widely acknowledged (Chatterjee et al. 2002; Zhu and Kraemer 2005), e-business adoption research accounts for a significant share of existing studies in this stream. However, some industries, countries, and e-business innovations lag behind others and, due to the importance of e-business adoption and use, a vast of new studies is published yearly to explain these differences (Chen and Holsapple 2012).

When designing new adoption studies, researchers often refer to a base model. For example, Zhu et al. (Zhu, Kraemer, and Xu 2006) build upon the technology-organization-environment (TOE) model and study e-business adoption in a cross-country context. Grandon and Pearson (2004) examine e-commerce adoption in small- and medium-sized companies, building upon the technology acceptance model (TAM), a predecessor of the unified theory of acceptance and use of technology (UTAUT), as a basis for their research. Cao et al. (2013) investigate Internet-enabled supply chain management systems. Their research is based on predictors derived from the task-technology-fit (TTF) model for innovation adoption. While each base model, i.e., TOE, UTAUT, and TTF, focuses on adoption through a different theoretical lens, interestingly, all three studies underline their decisions for the respective model with consistent empirical support found in prior studies; a discussion of why a specific model instead was chosen over any of the other models is missing. Other authors have already integrated firm-level adoption models. For example, Chan et al. (2012) integrate the TOE and UTAUT models to account for the strength of the different model backgrounds and to increase the overall predictive power; however, the explanatory contribution of each single base model remains unclear. While theoretical reviews on different adoption models such as Hameed et al. (2012) already endeavor in this direction and discuss strength and weaknesses at different stages of technology diffusion, empirical evidences are still missing.

Although the research stream on firm-level adoption is regarded as quite mature and we find empirical meta studies in the context of individual technology usage (Taylor and Todd 1995; Venkatesh et al. 2003), to the best of our knowledge, there is no comprehensive empirical comparison of the key competing models for firm level adoption. Thus, the need for a review and an empirical baseline assessment of existing theories in order to guide future researchers in their choice of a base model becomes apparent.

The primary purpose of this review is to assess the current state of knowledge with respect to the adoption of e-business at the firm level. This review is the first to empirically assess the similarities and differences of three base models. While, e.g., Hong and Zhu (2006) find more than 10 different theoretical lenses that have been used in e-business adoption research, we concentrate on three prominent and reoccurring models and discuss their similarities and differences: the TTF model with its predictors for the technology fit, the UTAUT model with its focus on individual perceptions of decision makers, and the TOE model offering a holistic perspective on the firm. We conduct an empirical within-subject validation and comparison of all three models using a data set of e-business adoption in the wood industry in Germany. Due to the expected variation of e-business diffusion, the wood industry is particularly suitable for this purpose. By using the explained variance of all models at each stage of e-business diffusion, this study contributes with a baseline assessment of the relative explanatory power of the individual models. In doing so, we provide two major contributions to the research community. First, future studies can use the empirical results when deciding for or against a base model for their e-business adoption studies. Second, we open the discussion about empirical research on different paradigms of looking at e-business adoption at the firm level and hope to inspire future studies following this direction.

1 Drawing on e-business literature, we define e-business as “using the Internet to conduct or support business activities along the value chain” (Zhu and Kraemer 2005). Furthermore, we consider e-business adoption as a multistage process that starts with initiation, which leads to initial adoption, and extends to routinization of e-business usage (Zhu, Kraemer, and Xu 2006). This is in contrast to studies that focus on single adoption decisions and, accordingly, try to explain “adoption or non-adoption” or adoption intentions.

2 We understand base models as so called factor-based adoption models, which specify causes of technology adoption in terms of a set of explanatory variables and their relation to dependent adoption variables (Kurnia and Johnston 2000).
The organization of the paper is as follows. In the next section, we review the process of IS adoption through the lens of diffusion of innovation theory and contrast TOE, TTF, and UTAUT in the context of firm-level adoption. Afterwards, we develop the research model and introduce the theoretical constructs underlying this study. The design and procedure of the empirical investigation by means of the structural equation modeling technique is outlined in the subsequent section. Results of the study including a data set of 204 organizations are then presented. The study closes with a discussion on findings, contributions, limitations, further research, and a conclusion.

**Background**

*Reviewing the IT innovation adoption process*

The adoption of an innovation is a process that results in the introduction and use of a product, process, or practice that is new to an adopting organization. This process has been categorized as a stage-based process (Hameed et al. 2012). Here, the various relevant stages considered in the IT literature will be discussed.

IT innovations such as e-business can be broadly defined as innovation in the organizational application of IT (Swanson and Ramiller 2004). The innovation diffusion theory (IDT), which has been the most widely used theoretical basis for the study of IT adoption (Hameed et al. 2012; Wu and Chuang 2010), provides insights into the dynamic and complex process of IT adoption and suggests that the diffusion of a technology will occur through different stages over time (Rogers 1995). However, initial research on IT adoption and diffusion has been focused on a single stage, which provides insufficient insights into the diffusion process (Zhu, Kraemer, and Xu 2006). More recently, researchers have made considerable efforts to increase the understanding of the innovation adoption process by categorizing the process of IT adoption in organizations into different phases and conducting multistage analyses. In particular, a number of studies have presented similar three-stage models in order to investigate various IT innovations. For example, academics have proposed models based on three stages to investigate the diffusion of general software practices (Zmud 1982), the incorporation of electronic scanners (Zmud and Apple 1992), as well as the diffusion of interorganizational systems, such as EDI (Premkumar et al. 1995), e-business, and e-collaboration (Chan et al. 2012; Zhu, Kraemer, and Xu 2006), or Web technologies (Ranganathan et al. 2004). Prior research has also revealed that the various stage-based frameworks with distinct numbers of stages follow similar and consistent patterns of diffusion that can be classified as the initiation stage, adoption stage and routinization stage (Wu and Chuang 2010). Based on the existing literature this research adopts these stages for the study of competing theories of IT adoption at the firm level for the ease of e-business.

According to IDT (Rogers 1995), the assimilation of an innovation starts with the initial awareness and evaluation of an innovation. The *initiation stage* comprises the identification and prioritization of organizational needs and problems as well as the search process within the organization’s environment to detect innovations of potential usefulness. The degree to which a located innovation fits organizational problems will influence the decision to adopt an innovation. IS literature also suggests that the potential of IT to enhance organizational performance is a significant driver for an organization to adopt IT (Armstrong and Sambamurthy 1999; Sethi and King 1994). Applying this view to our study, we define the first stage of e-business assimilation in accordance with Zhu et al. (2006) as evaluating the potential benefits to improve an organization’s performance. The stage of initiation is followed by the *adoption stage*. Consistent with IDT (Rogers 1995), this second stage reflects the adoption decision and involves the acquisition and implementation of a technology as well as the allocation of resources (Zhu, Kraemer, and Xu 2006). Prior studies have examined IT adoption decisions and found that adopters and nonadopters differ significantly in terms of external environments and internal resources (Chau and Tam 1997; Iacovou et al. 1995; Zhu et al. 2003). Since the adoption decision legitimizes resource allocation, this stage is a necessary step toward the widespread use of a technology. Therefore, we define the second stage of e-business assimilation –the adoption stage– as making the decision to use e-business and allocating the resources for acquisition and implementation. Following adoption is the *routinization stage*. According to previous work in the innovation field, adoption does not always result in the widespread use of a technology. Assimilation gap theory (Fichman and Kemerer 1999) implies that most information technologies exhibit an “assimilation gap,” which suggests that the widespread use of an
technology tends to lag behind its adoption. The existence of assimilation gaps has been reported in empirical studies on IT adoption and diffusion (Cooper and Zmud 1990; Fichman and Kemerer 1999). This research has an important implication: it states that adoption and routinization are two distinct stages (Zhu, Kraemer, and Xu 2006). Thus, we define e-business routinization—the third stage of e-business assimilation—as the stage in which e-business has gained both widespread and regular use, and has been accepted and institutionalized into an organization.

Based on the existing literature this research adopts the initiation, adoption, and routinization phases as the three stages of e-business assimilation in a study of competing theories of IT adoption at the firm level. The categorization of the innovation adoption process in organizations as a three-stage process is consistent with prevailing literature and offers theoretical support for our study.

**Reviewing existing adoption models at the firm level**

Thus far, no single or predominant innovation adoption theory exists, and it seems unlikely that a definitive one will evolve (Fichman 1999; Hong and Zhu 2006). However, researchers have been developing various frameworks, theories, and theoretical models to explain adoption behavior and adoption determinants in different contexts of IT. Within this area of inquiry, there have been various streams of research. While one stream of research focuses on individual acceptance of technology by using intention or use as a dependent variable, this research focuses on technology diffusion at the organizational level (Venkatesh et al. 2003). Therefore, we discuss three prominent competing theoretical models in innovation adoption literature on the firm level.

The TOE framework (Tornatzky and Fleischer 1990) has been approved for organizational-level studies of IT innovation adoption. The framework is consistent with IDT and emphasizes individual characteristics as well as both internal and external characteristics of the organization (Oliveira and Martins 2011). Further, it includes the environment context and allows IDT to better explain intraorganizational innovation diffusion (Hsu et al. 2006). The TOE framework has comprehensively gained empirical support. Various researchers have used the TOE framework or it with other theoretical models to investigate different IT adoptions, such as EDI (Kuan and Chau 2001), open systems (Chau and Tam 1997), ERP systems (Pan and Jang 2008), and e-business (Zhu and Kraemer 2005; Zhu et al. 2003; Zhu, Kraemer, and Xu 2006). Since TOE model presents a framework for technological-innovation decisions, it focuses on the first two stages of innovation assimilation (Hameed et al. 2012). The second model of technology adoption considered, the TTF model (Goodhue and Thompson 1995), postulates that if the technology fits the requirement of a task, it will improve the performance. In contrast to the TOE framework, the TTF model considers how the task affects usage (Pagani 2006). The fit is attributed to both task and technology characteristics. Thus, a technology will be adopted if the functions of a technology support the need of a task. The TTF model was originally developed to evaluate individual adoption behavior; however, it has been extended and used to empirically examine IT innovation adoption on both the group and organizational levels. Accordingly, IS researchers have studied the adoption of various technologies on the firm level, such as high-speed data services (Pagani 2006), technology-mediated distance education (Ozdemir and Abrevaya 2007), and supply chain management systems (Cao et al. 2013; Setia et al. 2008). Further, we have considered the theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003) as the third model of technology adoption. The theory integrates elements across eight acceptance models and has been empirically tested and validated in different domains (Taiwo and Downe 2013). In contrast to TOE and TTF, the theory summarizes constructs from various prominent acceptance models and has its roots in behavioral sciences (Venkatesh et al. 2003). Thus, UTAUT focus on user characteristics rather than on technology-oriented factors. The model received considerable attention in IS research and has been applied to study both technology adoption on the organizational level (Chan et al. 2012) as well as intraorganizational technology adoption, particularly examining the phase of routinization (Brown et al. 2010; Hameed et al. 2012). Thus, in contrast to TOE and TTF, it refers to both individual and organizational characteristics and facilitates a differentiated and broader perspective on the innovation assimilation process (Chan et al. 2012).
Table 1 displays the different determinants of IT innovation adoption suggested by Hameed et al. (2012) that affect the initiation, adoption, and routinization stages of e-business assimilation. Each of the theoretical models discussed involves various factors from different contexts and refers to the different determinants of IT innovation adoption. Hence, they support distinct stages of the innovation adoption process.

<table>
<thead>
<tr>
<th>Stage of adoption</th>
<th>Determinants of IT adoption</th>
<th>Theoretical model of IT innovation adoption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initiation</td>
<td>Innovation characteristics</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Adoption</td>
<td>Environmental characteristics</td>
<td>X</td>
</tr>
<tr>
<td>Routinization</td>
<td>Individual characteristics</td>
<td>X</td>
</tr>
</tbody>
</table>

X: fully supported; (X): partially supported

As the TOE model has been developed in order to examine the decision-making process, it concentrates on the adoption and pre-adoption phases of IT innovation assimilation (Hameed et al. 2012). Its constructs cover environmental and organizational as well as innovation-related determinants of IT adoption (Tornatzky and Fleischer 1990). In contrast to the TOE model, both TTF and UTAUT additionally cover individual characteristics of IT adoption determinants, such as perceived ease of use or expectancies regarding effort and performance (Hameed et al. 2012). Since the technology fit is attributed to both task and technology characteristics, the TTF model refers to both the initiation phase as well as the routinization phase (Cao et al. 2013). Against this, UTAUT examines both the intention to use a technology as well as the actual use. By combining various constructs from different prevailing theoretical models, such as the theory of reasoned action, technology acceptance model, motivational model, etc., Venkatesh et al. (2003) consolidate constructs that have significant influence on the adoption and use of technology (Cao et al. 2013). Hence, UTAUT claims to cover aspects of IT adoption determinants on all stages of the assimilation process, but it provides less support for innovation- and environmental-related characteristics than the TOE TTF.

**Research model**

This study empirically compares factor-based adoption theories in their explanatory power of IT assimilation at the firm level. The underlying assumption of factor-based theories is that explanatory variables can unidirectionally determine assimilation behaviors (Kurnia and Johnston 2000). Following this reasoning, factor-based theories specify a set of variables that explain why individuals have or have not assimilated IT. The term “individual” refers to the unit of analysis, which is the individual organization. The basic concept of this research is depicted in Figure 1.
We use three sequential stages of IT innovation assimilation as dependent variables; they form the basis for the empirical comparison. Our review of firm-level adoption models resulted in the identification of three competing models that found wide consideration in firm-level adoption studies. First, we use a prominent instance of the TOE framework that has been proposed by Zhu et al. (2006). It comprises seven explanatory variables: technological readiness, technological integration, firm size, global scope, managerial obstacles, competition intensity, and regulatory environment. Second, we use task-technology fit theory as a theoretical lens and build on a set of five variables as suggested in Cao et al. (2013): information quality, ease of use, system reliability, authentication, and compatibility. Finally, we examine the predictive power of UTAUT and its adoption determinants, i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions. The explanatory variables of the factor-based adoption models are described in Table 2.

<table>
<thead>
<tr>
<th>Table 2. Overview of Explanatory Variables</th>
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<tbody>
<tr>
<td><strong>Technology-Organization-Environment Model (derived from Zhu et al. 2006)</strong></td>
</tr>
<tr>
<td><strong>Technological readiness</strong></td>
</tr>
<tr>
<td><strong>Technological integration</strong></td>
</tr>
<tr>
<td><strong>Firm size</strong></td>
</tr>
<tr>
<td><strong>Global scope</strong></td>
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</table>
Managerial obstacles: Managerial obstacles can be defined as the lack of managerial skills for managing organizational adaptations to accommodate e-business within an organization (Zhu, Kraemer, and Xu 2006). E-business requires that firms undergo a digital transformation, bringing about unique challenges with regard to organizational adaptations that cannot be managed effectively by all firms (Chatterjee et al. 2002; Roberts et al. 2003). The ability to blend managerial and IT skills lies at the heart of a firm’s ability to assimilate information technology (Mata et al. 1995). It thus appears that when firms confront obstacles in making organizational changes, redesigning processes, and acquiring new expertise, it is difficult to achieve a smooth digital transformation and deep assimilation of e-business. Therefore, it can be proposed that an assessment of managerial obstacles is a significant barrier to e-business assimilation.

Competition intensity: Competition intensity is the extent to which a firm is affected by its competitors in the market (Zhu et al. 2004); its effect on e-business assimilation can vary throughout the assimilation process. Initially, competition could drive firms to adopt innovations such as e-business applications in order to maintain a competitive edge. E-business applications can help firms improve market responsiveness and information transparency (Zhu 2004), increase operational efficiencies (Zhu and Kraemer 2002; Zhu, Kraemer, and Xu 2006), and achieve customer lock-in (Shapiro and Varian 1999). Although competition is likely to drive firms to adopt e-business, competition might have a different effect on routinization. To routinize complex technologies, firms need deep technical and managerial skills beyond simple awareness of the innovation, which can be acquired mainly through a learning-by-using process (Fichman and Kemerer 1999). However, firms in a more competitive environment are driven by competitive pressure to leap rapidly from one technology to the next (Abrahamson 1991), making them less likely to undergo a gradual, careful, and sustained learning-by-doing process to develop skills for routinizing existing technologies (Mata et al. 1995). E-business is particularly prone to this pattern, which may impede its routinization.

Regulatory environment: The regulatory environment has been recognized as a critical factor influencing innovation diffusion (Zhu et al. 2003, 2004). The government can affect innovation diffusion in two ways: altering payoffs via taxes and other measures or changing the regulatory climate (Williamson 1983). The latter is particularly applicable to e-business, as companies often cite inadequate legal protection for online business activities, unclear business laws, and security or privacy concerns as common concerns for conducting e-business (Kraemer et al. 2006; Zhu, Kraemer, and Xu 2006). Accordingly, governments can encourage e-business assimilation with supportive regulations and policies in three areas: developing supportive legislation on key issues such as digital signatures, electronic transactions, and intellectual property; regulating the Internet to make it a trustworthy business platform by establishing privacy and consumer protection laws and dealing with fraud and credit card misuse; and providing incentives such as technical support, training, and funding for using e-business in government procurements and contracts (Kraemer et al. 2006).

Task Technology Fit (derived from Cao et al. 2006)

| Information quality | Information quality reflects the degree of accuracy of information generated by an IS. It is proposed as a construct of IS research and has been considered in distinct dimensions in several studies of IT adoption (Nelson et al. 2005). The construct combines four single dimension from the original TTF model proposed by Goodhue & Thompson (1995): data quality, locatability, timeliness, and usability. Data quality refers to the degree of currency, adequacy, and suitability of the level of data abstraction. Locatability indicates the ease of determining what data is available and where. Further, timeliness determines whether the IS meets predefined schedules, and usability reflects the relationship with users (Goodhue and Thompson 1995). All these constructs reflect different dimensions of information quality. Thus, consistent with prevailing research on e-business adoption we aggregate them into a single construct (Cao et al. 2013). Cao et al. 2013 find that appropriate information quality clearly impacts the initiation, adoption, and routinization stages of the IT innovation assimilation process. |
| Ease of use | Ease of use reflects whether a user is able to apply an IS in order to submit, access, and analyze data. The construct reflects aspects of use, such as convenience and simplicity, and further encompasses training- and learning-related aspects (Goodhue and Thompson 1995). Thus, the construct is similar to the perceived ease of use variable proposed by Davis (1989) in the original TAM model, which determines the degree to which a person believes that using a particular system would be free of effort (Davis 1989). Several previous studies find that the construct is a key determinant of user IT acceptance (Hameed et al. 2012). Therefore, the influence of this construct will be the strongest at the stage of routinization, where e-business has gained a widespread and a regular usage. Since the variable involves expectations, it also influences the initiation and adoption stages. |
Thus, this...system reliability influences the assimilation of e-business. Since the stage of adoption reflects the decision to accept an innovation and evaluates proposed ideas from a technical perspective (Hameed et al. 2012), system reliability will have a particularly strong impact during this stage of adoption.

Authorization determines to what extent users are properly authorized to obtain data relevant to the task from the corporate database (Lee et al. 2007). The construct reflects both the appropriate level of authorization as well as the effort needed to obtain authorization to access useful data (Goodhue and Thompson 1995). Since the availability of data facilitates task fulfillment, it is positively related with IT adoption and routinization. Cao et al. (2013) find that an appropriate degree of authorization can be seen as a predictor for the adoption of e-business.

Compatibility refers to the degree of consistency of data from two or more different resources (Lee et al. 2007). The construct indicates whether data from different sources can be consolidated and compared without inconsistencies (Goodhue and Thompson 1995). In accordance with IDT, the compatibility of an innovation with a potential adopter is, theoretically, positively related to the adoption and implementation of an innovation (Rogers 1995). Prevailing literature confirms that system compatibility has a significant influence on both e-business adoption and routinization (Cao et al. 2013).

**Unified Theory of Acceptance and Use of Technology (derived from Venkatesh et al. 2003)**

<table>
<thead>
<tr>
<th>Construct</th>
<th>Definition</th>
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<tr>
<td>Performance expectancy</td>
<td>Performance expectancy is the degree to which beliefs about using e-business will lead to gains in performance (Venkatesh et al. 2003). The construct is similar to the perceived usefulness variable proposed by Davis (1986) in the original TAM. Several studies on firm-level IT adoption find that performance expectancy has a significant and positive relationship with all three stages of the IT innovation adoption process (Chan et al. 2012).</td>
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<tr>
<td>Effort expectancy</td>
<td>Effort expectancy is defined as the degree of ease associated with the use of a system (Venkatesh et al. 2003). Venkatesh et al. 2003 derive the construct from preexisting adoption theories. It conflates substantially similar variables from preexisting technology adoption theories, such as TAM/TAM2 (perceived ease of use), MPDU (complexity) and IDT (ease of use). Previous research (Agarwal and Prasad 1998; Venkatesh et al. 2003) finds that the influence of effort expectancy on technology adoption will be more salient in early stages of the technology adoption process, declining in later phases. Consistent with empirical results (Chan et al. 2012), this can be explained by the initial unfamiliarity with e-business. Once e-business systems have become widespread and are routinely applied, other issues such as performance will become more crucial.</td>
</tr>
<tr>
<td>Social influence</td>
<td>Social influence is defined as the degree to which a potential adopter perceives that other important organizational members believe that e-business should be used (Venkatesh et al. 2003). Social influence can be seen as a direct determinant of behavioral intention. The construct is drawn up on the subjective norm, social factors, and image proposed by various researchers and adoption studies (Chan et al. 2012; Venkatesh et al. 2003). The support and influence from an organizations management as well as from peers has the potential to influence the utilization of e-business in all stages of the IT innovation adoption process (Chan et al. 2012) but has a more salient influence at pre-adoption stages (Karahanna et al. 1999) .</td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>Facilitating conditions are defined as the degree to which organizational and technical infrastructure exists to support e-business. Facilitating conditions include aspects of the technological and organizational environment that are designed to remove barriers to use (Venkatesh et al. 2003). The construct is very similar to the technology readiness variable, which has been used to study e-business adoption on an organizational level (Chan et al. 2012; Zhu, Kraemer, and Xu 2006). Zhu et al. (2006) argue that although technology readiness is necessary for all three diffusion stages, its effects should be greater during the adoption and routinization stages when compared to the first stage. However, empirical research has revealed that facilitating conditions are significantly positively associated with e-business adoption at all stages of the IT innovation adoption process (Chan et al. 2012; Zhu, Kraemer, and Xu 2006).</td>
</tr>
</tbody>
</table>
Comparing the Predictive Power of E-Business Adoption Models

Research design

Our research design for the comparison of competing IS adoption models in the context of e-business adoption uses the dependent variables – in our case, the three stages of e-business assimilation – as the common denominator for an empirical evaluation of the predictive power. This approach is consistent with prior research by Taylor and Todd (2003) and Venkatesh et al. (2003). More specifically, we used an online survey method to collect data from the German wood industry. Each subject answered a questionnaire covering all scales of the three sets of explanatory variables and the three stages of e-business assimilation. For the empirical comparison, we used the data and estimated the predictive power of each base model separately in order to compare the predictive power.

Measurement of constructs

The theoretical constructs that are the subjects of this study require operationalization. All scales for both the dependent and independent variables were adopted from previous research. The scales were translated to German and the result was cross-checked independently by two researchers. In addition, a focus group revised the questionnaire. The interviews did not yield any major changes for the scales; however, following some minor remarks regarding wording issues, have been implemented. An overview of the measurement instruments including all items (in English) can be found in the Appendix.

The three stages of innovation assimilation are measured according to Zhu, Kraemer, and Xu (2006). First, e-Business initiation is defined as the potential benefits of e-business, rated before the organization began to use it. It is measured with four items covering cost reduction, market expansion, new businesses entering, and supply chain coordination (4 items). Second, e-business adoption is based on the value chain model (Porter 1985) and measures whether an organization had used the Internet for each value chain activity as an aggregated value (1 item). Third, e-business routinization is defined as the extent of organizational use in their support of value chain activities. It is measured by the relative share of sales to consumers/businesses, total services to consumers/businesses, and total procurement (5 items).

The operationalization of the independent variables follows the original scales of the corresponding papers. The scales for the TOE model are adapted from Zhu, Kraemer, and Xu (2006). Accordingly, technological readiness (3 items), technological integration (2 items), firm size (1 item), managerial obstacles (3 items), competition intensity (3 items), and regulatory environment (4 items) are modeled as reflective constructs. Global scope comprises two sub-dimensions, i.e., geographic scope (3 items) and trading globalization (2 items), and is operationalized as a reflective second-order construct. The scales for the TTF model are adapted from Cao et al. (2013) and entail information quality (3 items), ease of use (3 items), system reliability (2 items), authentication (2 items), and compatibility (3 items). The measures for the UTAUT constructs are derived from Venkatesh et al. (2003) and include the four reflective scales performance expectancy (3 items), effort expectancy (4 items), social influence (4 items), and facilitating conditions (4 items).

Sample and non-response bias

The assimilation of e-business in the wood industry was chosen as the unit of analysis for this study. This specific industry is suitable as the starting point for our empirical analysis for two reasons: First, the wood industry exhibits a generally low to medium rate of IS diffusion (Arano and Spong 2012; Karuranga et al. 2005; Vlosky and Smith 2003), which usually corresponds with low investments in IS (Arano 2008). While mature industries may have a generally high degree of e-business use and therefore display less variance at the different levels of e-business diffusion, we expect to see a high degree of variance for the wood industry. Second, despite the comparably low to medium diffusion of IS, studies such as Perkins (2009) demonstrate the importance of technological integration through information systems for the specific case of the wood industry. Given the low to medium diffusion of IS and its fundamental potentials, we argue that the wood industry is a suitable starting point for analyzing the quality of predictors for e-business diffusion. A comprehensive review of IS diffusion studies in the wood industry can be found in Hewitt and Paradi (2011).

Respondents from German wood companies were gathered using an online survey method between November 2013 and February 2014. The link was distributed among companies involved in woodworking,
wood processing, wood building, or the timber trade that were listed on the website of the Internationale Holzbörse (IHB). The IHB is a sector network that is specialized in the forestry and wood cluster and provides a business database with contacts. In addition, personalized survey invitations were sent out. This lead to a total of 312 completed questionnaires. From these cases, 108 were excluded due to quality criteria such as missing values, the implausibility of firm characteristics, and IT usage behaviors. Overall, 204 complete cases that fulfilled all quality criteria were collected. The sample characteristics are summarized in Table 3.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Respondents title</th>
<th>Age of respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woodworking industry</td>
<td>CEO, CIO, CTO</td>
<td>18-25 years</td>
</tr>
<tr>
<td>Wood processing industry</td>
<td>Senior manager</td>
<td>26-38 years</td>
</tr>
<tr>
<td>Wood building industry</td>
<td>Senior IT manager</td>
<td>39-45 years</td>
</tr>
<tr>
<td>Timber trade</td>
<td>18.8%</td>
<td>&gt;45 years</td>
</tr>
</tbody>
</table>

Table 3. Sample Characteristics

Low return rates are typical for this kind of web-based survey (Preston and Karahanna 2009). However, low response rates bear the risk of non-response; we therefore use two common measures to account for this threat. First, the sample has characteristics similar to the basic population, indicating that our sample is representative for the population. Second, we compare the mean values of the answers (latent variable scores) of the first third and the last third of the sample (Armstrong and Overton 1977). A t-test revealed non-significant differences (at a significance level of $p<.05$). Both indicate that non-responses are not a major threat for this study.

Data analysis and results

In order to test the theoretical model, a SEM approach was used. We decided on the partial least squares method (PLS) because it has fewer demands for sample size and excels at prediction (Ringle et al. 2012), which is the primary focus in this paper. Our analysis was supported primarily using the software SmartPLS 2.0.M3. We used SPSS Statistics 21 for tests that are not available in the SmartPLS packages.

The data analysis of each model follows the widely adopted two-step approach to structural equation modeling espoused by Anderson and Gerbing (1988). In order to ensure the validity and reliability of the instruments, we first assessed the quality of the data and each measurement model. We then analyzed each structural model separately. Finally, we conducted a cross-model comparison by comparing the mean differences of the explained variance at each step of the innovation process.

Common method bias and measurement validation

According to Barclay et al. (1995), the sample size should exceed 10 times the number of maximum arrowheads pointing to a latent variable; this holds for both the structural model and the measurement model. Our sample size, which includes 204 cases, meets both criteria.

As a single informant assessed both independent and dependent variables in our model, common method variance (CMV) poses a potential threat to the validity of the results (Podsakoff and MacKenzie 2003). We checked for CMV with the Harman’s single factor test and ran an exploratory factor analysis. Not a single factor emerges from the data, and a general factor does not account for the majority of the covariance among the measures. The result suggests that common method bias is not a major concern in this study.
In order to assess the fit of the hypothesis and empirical data, all three measurement models were tested for content, convergent, and discriminant validity. Content validity refers to the degree to which a construct measures all facets of the underlying social construct. We assured content validity by using established theories and existing scales from IS. Convergent validity refers to whether items measuring a construct correspond with one another. Three measures for convergent validity were evaluated for each reflective measure: individual item reliability, composite construct reliability (CR), and average variance extracted (AVE). Due to low factor loadings, we dropped one item each from the technological readiness, competition intensity, regulatory environment, and facilitating conditions scale. Afterwards, as depicted in Table 6, most items loaded on its own construct at .70 or above, which indicates an acceptable limit of individual item reliability (Gefen and Straub 2005). The CR varies between .790 and .953, i.e., above the acceptable limit of .70 (Hulland 1999). All AVEs also exceeded the lower bound of .50 (Bhattacherjee and Premkumar 2004). Discriminant validity refers to whether theoretically distinct concepts are empirically distinct from one another; we used the criterion of Fornell and Larcker (1981) to assess this quality. For each model, the AVE for each construct is greater than the variance shared with other constructs (see square root AVEs on the diagonal in Tables 4, 5, and 6), confirming discriminant validity. Last, we checked cross-loadings and, as expected, all items have higher loadings on their assigned construct than...
on the other constructs in each model (Chin 1998). Our analyses suggest that our measurement model is both acceptable and reliable.

**Structural models**

As we aim to examine the prediction of the different levels of the IS assimilation process and indirect paths do not affect the variance explained, we only modelled the direct effects of the three models. After we ran the PLS algorithm for estimating the structural model, we used the bootstrapping re-sampling method to compute inference statistics. Bootstrapping is the preferred method if the sample size is greater than 100 (Kock 2011). An overview of the estimations for all three models can be found in Table 7.

When interpreting the explained variance, acceptable levels depend on the research context (Hair et al. 2011). While behavioral models on individual technology usage can exhibit an R-squared value of up to 76 percent (e.g., Venkatesh et al. 2003), firm-level adoption studies usually display lower values. The structural models in this study can explain of .111 to .267 of the variance in the dependent variables. Compared to other studies on firm-level e-business use these results can be regarded as low to average (e.g., (Zhu and Kraemer 2005)). This comparably lower R-squared value is not surprising since we used base models and no further extensions that are specific to the context. Moreover, the focus of this study is to compare predictive power among the theories.

Table 7. Path Coefficients of the Structural Models

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Dependent variable</th>
<th>Initiation</th>
<th>Adoption</th>
<th>Routinization</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technological readiness</td>
<td>.105</td>
<td>.359***</td>
<td>.284**</td>
<td></td>
</tr>
<tr>
<td>Technological integration</td>
<td>.108</td>
<td>.236***</td>
<td>.159*</td>
<td></td>
</tr>
<tr>
<td>Firm size</td>
<td>-.098</td>
<td>-.064</td>
<td>-.219**</td>
<td></td>
</tr>
<tr>
<td>Global scope</td>
<td>.055</td>
<td>-.010</td>
<td>-.227**</td>
<td></td>
</tr>
<tr>
<td>Managerial obstacles</td>
<td>-.075</td>
<td>-.062</td>
<td>-.148*</td>
<td></td>
</tr>
<tr>
<td>Competition intensity</td>
<td>.193**</td>
<td>.183**</td>
<td>.092</td>
<td></td>
</tr>
<tr>
<td>Regulatory environment</td>
<td>.155*</td>
<td>-.051</td>
<td>.053</td>
<td></td>
</tr>
<tr>
<td>TTF</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information quality</td>
<td>.312***</td>
<td>.201***</td>
<td>.111*</td>
<td></td>
</tr>
<tr>
<td>Ease of use</td>
<td>.068</td>
<td>.024</td>
<td>.023</td>
<td></td>
</tr>
<tr>
<td>System reliability</td>
<td>-.007</td>
<td>.022</td>
<td>.042</td>
<td></td>
</tr>
<tr>
<td>Authentication</td>
<td>.033</td>
<td>.041</td>
<td>-.031</td>
<td></td>
</tr>
<tr>
<td>Compatibility</td>
<td>.163***</td>
<td>.323***</td>
<td>.271***</td>
<td></td>
</tr>
<tr>
<td>UTAUT</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Performance expectancy</td>
<td>.344***</td>
<td>.244**</td>
<td>.278***</td>
<td></td>
</tr>
<tr>
<td>Effort expectancy</td>
<td>-.015</td>
<td>-.014</td>
<td>.149</td>
<td></td>
</tr>
<tr>
<td>Social influence</td>
<td>.216**</td>
<td>.079</td>
<td>.183*</td>
<td></td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>.082*</td>
<td>.372***</td>
<td>.272**</td>
<td></td>
</tr>
</tbody>
</table>

Significance levels: **p<.01, ***p<.05, *p<.10

All variables of the TOE were significant on at least one level in the process of technology assimilation. In the case of the TTF model, ease of use, system reliability, and authentication found no support in any step. For the UTAUT model, only effort expectancy found no significant support.

**Model comparison**

After estimating each model separately, we compared the results. The models differ in their number of explanatory variables. Since the explained variance increases with the number of explanatory variables and this is independent from their explanatory power, we also computed adjusted R-squares. This correction of the models’ explanatory power allowed us to compare the different theories.
We decided to use a parametric approach to test for mean differences of the R-squared value among the three models. The procedure we chose generally follows the logic of Chin’s (2000) parametric approach for multigroup analysis in PLS. First, a sample of each subpopulation is analyzed, resulting in groupwise estimates of all model parameters. Second, group differences are evaluated. According to this proceeding, we calculated the R-squared value for each model and each process stage. Afterwards, we used bootstrapping to obtain distributions for the R-squared values. Based on these results, we used a one-way analysis of variance (ANOVA) to test whether the groups are drawn from the same population. For all three stages of the assimilation process, the results of the ANOVA reject the null hypothesis. The results of our computations are depicted in Table 8.

The TOE model performs equally well for the adoption (R-squared adj.=.239) and routinization stage (R-squared adj.=.241); for the initiation it can only explain .100 percent of the variance. The UTAUT model shows comparably good results in all three stages with an adjusted R-squared value between .233 and .257. The TTF performs best in the adoption stage (R-squared adj.=.179), followed by the initiation stage (R-squared adj.=.162) and, lastly the routinization stage (R-squared adj.=.089). All R-squared are significantly different from zero.

**Discussion**

This study addresses an important gap in current firm-level adoption research. While existing literature on e-business adoption provides a variety of theoretical lenses and base models (Hong and Zhu 2006), there is no study that reveals differences in the explanatory power; however, this is important for model selection in e-business adoption studies (Chen and Holsapple 2012). Therefore, the primary purpose of this review was to empirically assess and compare three prominent foundational models. The results of the within-subject analysis reveal interesting insights into the predictive power of the different theories.

First of all, our data exhibit a comparably low predictive power of the TOE model at the initiation stage. This holds for both the comparison within the different stages of e-business adoption and between the models within the initiation stage. While TTF can explain .162 of the variance, UTAUT best explains the initiation. The strength of TTF, i.e., the focus on the fit between technology and task characteristics, and that of UTAUT, i.e., the focus on the decision maker, were revealed to be better predictors for the potential to improve an organization’s performance. On the adoption stage, which reflects the decision to use e-business and allocating the resources for acquisition and implementation, UTAUT again performs best; however, the TOE model displays almost equally good results. Finally, e-business routinization can be best explained by the TOE model, followed by UTAUT; TTF has only a low explanatory power, with a value below .100.

Second, the explanatory powers of the TOE model show good results at the adoption and routinization stages, with comparatively worse results at the initiation stage. We find an opposite effect when looking at the TTF model; here we find relatively stable values at the initiation and adoption stages. Finally, in our data set the UTAUT model is revealed to have relatively stable explained variance across all stages. This characteristic of stable R-squared values becomes particularly important when examining differences between the stages, for example, when trying to explain the assimilation gap.

Third, while UTAUT exhibits stable variances across all stages, it is also revealed to have comparably high explanatory power. In the first stage, it has the highest R-squared value, while the results are similar to the TOE model in the second and third stages. This is interesting, as UTAUT is also the model with the lowest number of explanatory variables. Following the goal of parsimony, model choice should consider good predictive power while keeping the number of predictors low (Bagozzi 1992). Only following this
principle, UTAUT seems to be preferable. However, all three models differ in their roots and focus and thus, depending on the research context, models should be “evaluated in terms of both parsimony and their contribution to understanding” (Taylor and Todd 1995).

Fourth, the choice of a base-line model can only explain part of the variation in e-business adoption. While there is considerable variation in the R-squared value among e-business adoption studies (Chan et al. 2012; Zhu, Kraemer, and Xu 2006), we do not find much variation between the different models in all stages of the process. In the initiation stage, the difference between the highest and the lowest adjusted R-squared is .152, in the adoption stage .078, and in the routinization stage .152. Other literature on model comparison of technology adoption also finds similar results in their dependent variables. For example, in their study on the technology use of individuals, Taylor and Todd (1995) find a maximal variation of .08 in intention to use and .02 in use behavior between three models; in a similar context, Venkatesh et al. (2003) find a maximal variation of .17 between 8 base models. An explanation is that the context, in which the study is conducted, is of particular importance. This is consistent with prior research which supports the argumentation that context-specific factors that are not covered in the base models account for a relevant share of the R-squared. In the context of e-business adoption, this can include industry types (Theodosiou and Katsikea 2012), country specifics (Zhu et al. 2003), or technology-specific explanations such as network effects (Zhu, Kraemer, Gurbaxani, et al. 2006).

Fifth, when deciding for or against a base model for an adoption study, explanatory power should of course not be the first and only criteria. Although our results revealed that each model has different empirical strength at different stages of adoption, the models are grounded in different in theoretical lenses and have different theoretical emphases. Accordingly, when designing a new adoption study, theoretical considerations should be decisive in the first place.

Lastly, although this study is primarily directed at researchers, practitioners can also draw important conclusions from the results. The data underlines the relevance of differentiating stages of e-business adoption. When decision makers aim to promote e-business, actions should be designed along the stages and their respective important factors. The regulatory environment, for example, was revealed to be important for the initiation but becomes insignificant for the routinization stage; on the other hand, managerial obstacles do not influence initiation and adoption but are an important inhibitor of e-business routinization. Moreover, as we find that all three models are limited in their explanatory power, decision makers should pay close attention to the specific context in which they are involved. Internal and external contingencies are particularly relevant and should be identified and addressed by management practices for a successful adoption of e-business.

When interpreting the results, limitations should be considered. First of all, we designed this initial study as a within-subject analysis and decided to test the different theories in the specific context of the German wood industry. While we argued this industry to be suitable as a starting point for our analysis as a narrow context allows for reducing the influence of uncontrolled variables, a specific context usually makes it harder to generalize. It is acknowledged that cultural differences (Zhu, Dong, Xu, et al. 2006) or industry specifics (Theodosiou and Katsikea 2012) can influence e-business adoption. This especially holds as we compare theories from different paradigms of looking at innovation adoption. Future research should conduct empirical studies in a broader range of industries and countries to validate the findings. Second, in order to compare the different theories, we used prominent instances of each theory. Especially in the case of the TOE, we found a wide range of differing models and extensions. Although the instance we chose, i.e., Zhu, Kraemer, and Xu (2006), has found wide consideration in IS research, other instances may provide better predictive power. An overview of other typical predictors can be found in Hameed et al. (2012). Third, studies that build on one of the analyzed theories often integrate further theoretical lenses, which not only add predicting variables but also suggest changing existing relationships. For example, Cao et al. (2013) add network effects as a moderator for the TTF relationships. While this study concentrates only on direct effects, future studies should consider moderated relationships. Despite these limitations, we see this study as a first step into an empirical cross-model comparison.

Conclusion

E-business adoption studies often argue their base model choice with empirical support they find in prior studies without discussing further theoretical lenses and their usage as base model. This study is the first
Comparing the Predictive Power of E-Business Adoption Models

that empirically tested and compared three prominent theories which are often used in the context of e-business adoption at the firm level. The results of a within-subject analysis in the German wood industry with 204 data points demonstrate that the TOE, TTF, and UTAUT models have different strengths at different stages of adoption. Interestingly, the most parsimonious model, i.e., UTAUT with four explanatory variables, exhibits the best predictive power among all stages. Future research on e-business adoption can use these results to guide them when deciding for or against a theoretical lens. However, the results also suggest that the choice of a base model plays only a limited role when aiming for high R-squared values. Further context-specific causes, which, e.g., have their roots in the technology, the industry, or in other country characteristics, seem to be particularly relevant in e-business adoption studies. While this study is grounded in the literature of e-business adoption at the firm level and empirically tested the case of e-business adoption, results are also interesting for other areas of technology adoption at the firm level. As this single within-subject study is a first step into the empirical comparison, we hope to inspire future studies following this path and empirically examine the similarities and differences among firm-level adoption theories.

References


Comparing the Predictive Power of E-Business Adoption Models


## Appendix

<table>
<thead>
<tr>
<th>Construct</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Process of Innovation Assimilation</strong></td>
<td>(adapted from Zhu 2006)</td>
</tr>
<tr>
<td>E-Business initiation</td>
<td>Please indicate how significant each of the following potential benefits of e-business was rated when your organization was considering using the Internet for value chain business activities: 1. To reduce costs, 2. To expand the market for existing products/services, 3. To enter new businesses or markets, 4. To improve coordination with customers and suppliers.</td>
</tr>
<tr>
<td>E-Business adoption</td>
<td>Check the box describing applications of the Internet in your value chain processes: Advertising and marketing, Making sales online, After-sales customer service and support, Exchanging operational data with upstream suppliers, Making purchases online, Exchanging operational data with downstream business partners and customers, Electronically integrating business processes with business partners (e.g., real-time transaction of orders, collaborative forecasting, integrated channel management, etc.).</td>
</tr>
<tr>
<td>E-Business routinization</td>
<td>1. What percent of your total sales to consumers are conducted online (i.e., the Internet)? 2. What percent of your total sales to businesses are conducted online? 3. What percent of your total services to consumers are conducted online? 4. What percent of your total services to businesses are conducted online? 5. What percent of supplies and equipment for doing business are ordered online?</td>
</tr>
<tr>
<td><strong>Technology-Organization-Environment Model</strong></td>
<td>(adapted from Zhu 2006)</td>
</tr>
<tr>
<td>Technological readiness</td>
<td>1. Approximately how many personal computers are currently in use in your organization? 2. Approximately how many IT professionals are located in your organization? 3. Please check the box describing technologies used in your organization (Use of e-mail, Use of websites accessible by public, Use of Intranet, Use of Extranet, Use of electronic data interchange (EDI), Use of electronic funds transfer (EFT), Use of a call center).</td>
</tr>
<tr>
<td>Technological integration</td>
<td>1. Your Internet systems are electronically integrated with your internal databases and information systems. 2. Your company’s databases and information systems are electronically integrated with those of your suppliers and business customers.</td>
</tr>
<tr>
<td>Firm size</td>
<td>1. Approximately how many employees does your organization have in total, including all branches, divisions, and subsidiaries?</td>
</tr>
<tr>
<td>Geographic Scope</td>
<td>1. Please check the box that describes the geographic extent of your operations: Your organization has more than one establishment, Your organization has establishments outside your country, Your organization has headquarters outside your country.</td>
</tr>
<tr>
<td>Trading Globalization</td>
<td>1. Approximately what percent of your total sales are from outside your country? 2. Approximately what percent of your total procurement spending is from outside your country?</td>
</tr>
<tr>
<td>Managerial obstacles</td>
<td>Please rate how significant the following obstacles are to your organization’s ability to conduct e-business (7-point Likert scale): 1. Making needed organizational changes for e-business implementation, 2. Integrating the Internet into your overall strategy and business process, 3. Lacking staff with e-business expertise.</td>
</tr>
<tr>
<td>Competition intensity</td>
<td>Please rate the degree to which your business activities are affected by: 1. Competitors in your local area, 2. Competitors inside your country, 3. Competitors from outside your country.</td>
</tr>
<tr>
<td>Regulatory environment</td>
<td>1. The use of the Internet for business was driven by incentives provided by the government, 2. The use of the Internet was required by government procurement, 3. Business laws support e-business, 4. There is adequate legal protection for Internet purchases.</td>
</tr>
<tr>
<td><strong>Task Technology Fit</strong></td>
<td>(adapted from Cao et al. 2013)</td>
</tr>
<tr>
<td>Information quality</td>
<td>1. The data provided by the e-business system is up to date enough for my purposes, 2. The e-business system available to me contains critical data that are very useful to me in my job, 3. The e-business system maintains data at an appropriate level of detail for my group’s tasks, 4. The exact definition of data fields relating to my tasks is easy to find out.</td>
</tr>
<tr>
<td>Ease of use</td>
<td>1. It is easy to learn how to use the e-business system, 2. The e-business system I use is convenient and easy to use, 3. There is a lot of training for me or my staff on how to find, understand, access, and use the e-business system.</td>
</tr>
</tbody>
</table>
### E-Business

<table>
<thead>
<tr>
<th>System reliability</th>
<th>1. The e-business system I use is not subject to unexpected or inconvenient down times that make it harder to do my work, 2. The e-business system I use is not subject to frequent system problems and crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Authorization</td>
<td>1. Data that would be useful to me are available because I have the right authorization, 2. Getting authorization to access data that would be useful in my job is easy and convenient</td>
</tr>
<tr>
<td>Compatibility</td>
<td>1. The e-business system is compatible with other existing information systems that serve business processes, 2. The e-business system is compatible with our IT infrastructure (e.g., IT network and IT security), 3. The use of the e-business system is in line with our basic IT policy and practices</td>
</tr>
</tbody>
</table>

**Unified Theory of Acceptance and Use of Technology (adapted from Venkatesh et al. 2003)**

<table>
<thead>
<tr>
<th>Performance expectancy</th>
<th>1. I would find an e-business system useful in my job, 2. Using e-business systems enables me to accomplish tasks more quickly, 3. Using e-business systems increases my productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effort expectancy</td>
<td>1. My interaction with the e-business system would be clear and understandable, 2. It would be easy for me to become skillful at using the e-business system, 3. I would find the e-business system easy to use, 4. Learning to operate the e-business system is easy for me</td>
</tr>
<tr>
<td>Social influence</td>
<td>1. People who influence my behavior think that I should use e-business systems, 2. People who are important to me think that I should use e-business systems, 3. The senior management of this business has been helpful in the use of e-business systems, 4. In general, the organization has supported the use of e-business systems</td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>1. I have the resources necessary to use e-business systems, 2. I have the knowledge necessary to use e-business systems, 3. The e-business system is not compatible with other systems I use, 4. A specific person (or group) is available for assistance with e-business system difficulties*</td>
</tr>
</tbody>
</table>

* Note: * Item has been removed due to low factor loadings.

**Acknowledgements**

This research was supported by the German Research Foundation (DFG), grant GRK 1703/1 for the Research Training Group “Resource Efficiency in Inter-organizational Networks – Planning Methods to Utilize Renewable Resources.”