The Effect of Learning on the Effective Use of Enterprise Systems

Abstract

Enterprise systems must be used effectively to maximize their benefits. Given their complexity and integration of standard business processes, they pose significant challenges for employees’ learning. Users need to learn how to access a system and its data and how to leverage the information it provides to perform their daily tasks effectively. Based on a literature review, we identify three context-oriented forms of learning, which affect a user’s level of effective use: learning via instruction, self-learning, and learning via social interaction. We aim to conduct a longitudinal case study to explore learning during an implementation project and develop a research model to measure the effect of learning on individuals’ effective use of an enterprise system. The extension of the nomological network of the concept of effective use by an integration of the effect of different forms of learning will be the main contribution of our research.

Keywords: Forms of Learning, Learning Context, Effective Use, Enterprise System, Training

Introduction

The implementation of an information system (IS) still represents a major challenge for many organizations. Especially the implementations of complex ISs, such as enterprise systems (ESs), often exceed budgets, take significantly longer than estimated, or even fail (Markus and Tanis 2000; Umble et al. 2003). In 2012, U.S. organizations spent approximately $164.2 billion on employee training, particularly to support ES implementations (ASTD Research 2013). However, even if these systems are implemented on time and within budget, expected benefits are often not realized (Boudreau and Seligman 2005; Boudreau 2003). One reason for this may be that a technology “per se can’t increase or decrease the productivity of workers’ performance” (Orlikowski 2000, p. 425), instead it “must be used effectively to obtain maximum benefits” (Burton-Jones and Grange 2013, p. 632). However, most theories of IT acceptance and use (e.g., TAM (Davis 1989); UTAUT (Venkatesh et al. 2003)) examine why individuals use a technology based on behavioral beliefs and neglect other important user behaviors such as learning (Benbasat and Barki 2007). Furthermore, traditional IS research has applied simplistic conceptualizations of use (e.g., frequency or duration), which cannot capture the richness of individuals’ system use (Benbasat and Barki 2007; Burton-Jones and Straub 2006). Given the complexity and risks of ES implementations (Devadoss and Pan 2007; Markus and Tanis 2000), it is important to go beyond lean measures of system use and to further analyze the complexity of IT use processes (Barki et al. 2007; Burton-Jones and Straub 2006).
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Recent advances in IS research highlight the importance of user adaptation and learning for the effective use (EU) of ISs (Burton-Jones and Grange 2013). Users can adapt the technology, the task, or themselves (i.e., through learning) (Barki et al. 2007; Beaudry and Pinsonneault 2005; Burton-Jones and Grange 2013). Learning allows users to make educated adaptations, which are more effective in raising their level of EU than uneducated adaptations (Burton-Jones and Grange 2013). Learning is particularly important in an organizational context due to the complex nature of ESs. ESs refer to all large organization-wide packaged applications, such as enterprise resource planning (ERP) or customer relationship management (CRM) systems (Seddon et al. 2010). ESs allow only little individual technical adaptations after the implementation (Boudreau and Robey 2005). Also, these systems automate and integrate best-practice business processes which can neither be modified by individual users (Boudreau and Robey 2005; Saeed and Abdinnour 2013). Given the complexity of ESs, along with the fact that adaptations of system or tasks are rarely possible, ESs pose significant challenges for individual learning (Boudreau and Robey 2005; Yamauchi and Swanson 2010). Employees inevitably need to learn how they can effectively use the system to do their job (Burton-Jones and Grange 2013; Sykes et al. 2009). Typically, the ongoing learning process starts when users receive basic instruction in training sessions before a new ES is rolled out (Sykes 2015) but they continue learning to use the system while they incorporate it in their day-to-day activities (Boudreau and Seligman 2005). Initially, users need to divert a significant amount of time to learn components of the new system (e.g., its user interface) (Burton-Jones and Grange 2013) and newly introduced business processes (Robey et al. 2002). On their own initiative, they explore a new system’s features or additionally available materials, such as manuals or online tutorials (e.g., Barki et al. 2007; Liang et al. 2015; Saeed and Abdinnour 2013), experiment with unknown features (e.g., Spiteri 2005; Tennant et al. 2015) or discover new ways of exploiting the system by trial and error (Beaudry and Pinsonneault 2005). Furthermore, users communicate with peers or support staff to learn better ways to accomplish their work (e.g., Bruque et al. 2008; Nan 2011; Sykes et al. 2009). In sum, learning opportunities are provided in different contexts and at different points in time during an ES’s implementation process.

According to Burton-Jones and Grange (2013), users need to learn how to access a system, how to obtain faithful representations during the interaction and how to leverage them. To achieve a high level of EU, it is not sufficient to learn how to interact with a system (i.e., which buttons to push) through learning its surface structure only (i.e., its user interface) (Boudreau and Robey 2005). Instead, users need to learn the logic behind the system (i.e., deep structures). However, it has not been clarified in which contexts users engage in learning and how this behavior ultimately affects the different dimensions of the EU construct and their level of EU overall. Thus, we aim to contribute to research with an extension of the nomological net of EU by refining the understanding of the effect of learning. Hence, we pose the following research question: How do different forms of learning impact a user’s ability to achieve effective use of an enterprise system?

In this research-in-progress paper, we begin to explore this question by conceptually exploring the links between learning and effective use and by proposing respective hypotheses. These serve as a foundation for a future longitudinal case study in an organization which currently performs a large ES implementation program. The remainder of this paper is organized as follows. Section two introduces the theoretical foundations which are used for the development of our hypotheses. In section three, we present our research model and formulate five hypotheses concerning the effect of the conceptualized learning forms. We then present our research design, covering both the steps already taken as well as the intended research still to come. Finally, we conclude with a discussion of next steps and intended contributions.

Theoretical Background

The Concept of Effective Use

Answering the call for a deeper conceptualization of individual IS use, Burton-Jones and Grange (2013) developed a theory that explains the nature and the drivers of EU. Their theory builds on representation theory, which states that ISs consist of three layered structures: surface structure (e.g., the user interface), physical structure (e.g., computer, networks, input/output devices), and deep structure (i.e., the system logic) (Burton-Jones and Grange 2013; Wand and Weber 1995). Deep structures convey the specification of real-world entities, such as objects, properties or states, and are populated with tokens during operation. These tokens are instances of the real-world entities defined in the deep structure (Parsons and Wand 2008). In other words, tokens are the actual data of the system stored in its database. Representations, however, are the combination of deep structure and tokens and should faithfully represent a real-world domain (Weber 1997). For example, a
CRM system represents the domain of an organization’s interaction with existing and potential future customers. One representation in this system is a customer. The properties of the real-world entity “customer” have been specified in the system’s deep structure (e.g., a customer has a name and can have several contacts assigned to her/him). When users create a new customer in the CRM system, they populate the system’s database with a new token (e.g., customer name, address, phone number, etc.). Representation theory assumes that users desire faithful representations because these provide a more informed basis for action than unfaithful representations do (Burton-Jones and Grange 2013). Burton-Jones and Grange (2013) define EU as “using a system in a way that helps attain the goals for using the system” (p. 633). They stress that IS are never used just to use them, but to achieve other goals (e.g., to look up customer information in a CRM system). EU is conceptualized as an aggregate construct which comprises three hierarchical dimensions: transparent interaction (TI), representational fidelity (RF) and informed action (IA). A user’s overall level of EU is determined by her/his aggregate levels of the three dimensions (Burton-Jones and Grange 2013). TI refers to the “extent to which a user is accessing the system’s representations unimpeded by its surface and physical structures” (Burton-Jones and Grange 2013, p. 642). RF is defined as the “extent to which a user is obtaining representations from the system that faithfully reflect the domain being represented” (Burton-Jones and Grange 2013, p. 642). IA reflects the “extent to which a user acts upon the faithful representations he or she obtains from the system to improve his or her state [in the domain]” (Burton-Jones and Grange 2013, p. 642). Users of a CRM system need to have accurate customer information, such as what products a customer might be interested in based on the purchase history (RF), to be able to send her/him a suitable offer (IA). If the customer accepts this offer, the employee may receive a commission for the sale and increase her/his income.

Furthermore, Burton-Jones and Grange (2013) identify two major drivers of EU: adaptation and learning. Adaptations are all actions that users take to improve the system’s representations or their access to them through physical and surface structures (e.g., personalize the user interface). In contrast, users can also take a system “as is” and engage in learning, which is the main focus of this paper. With the effect of adaptations already being addressed elsewhere (Haake et al. 2015), we aim at extending our work introduced here by accounting for the interplay of learning and adaptation patterns at a later stage. Since IS consist of a complex set of structures, it is necessary to learn how to interact with them. Due to the fallibility of representations, users also need to learn to trust a representation before making an effort to obtain and act on it. Burton-Jones and Grange (2013) propose several learning actions, which include all activities to learn the system (i.e., its physical/surface structure and representations), the domain it represents, the fidelity of its representations, and how to leverage the obtained representations. These learning actions are theorized to improve a user’s ability to effectively use a system by influencing one or more dimensions of the EU construct (see Figure 1).

The theory of EU refers to ISs in very broad terms, and not only to ESSs specifically. Using the IS categorizations by McAfee (2006) and Borgmann (1999), Burton-Jones and Grange (2013) demonstrate how their theory can be applied to different types of ISs. In the conceptual development of our research model, we maintain the broad scope of their original model. However, the setting in our case organization only allows for an examination of an ES, a category of ISs that touches upon multiple categories discussed by Burton-Jones and Grange (2013). We will reflect upon the resultant limitations of our empirical work and plans for future extensions later, but maintain that the conceptual development offered in this paper’s first part remains true to Burton-Jones’ and Grange’s (2013) original scope.

The Concept of Learning

Psychologists have extensively studied human learning processes and developed various competing learning theories based on behaviorist, humanist, cognitivist, social cognitive, or constructivist approaches (Merriam et al. 2012). We adopt the definition of learning as “a process that brings together cognitive, emotional, and environmental influences and experiences for acquiring, enhancing, or making changes in one’s knowledge, skills, values, and world views” (Merriam et al. 2012, p. 277). From the literature, three main facets of learning can be identified: forms of learning, learning subject, and factors influencing learning. The following contextualizes these against our studies core phenomenon, that is, learning to effectively use an IS.

Forms of learning: Learning to effectively use an IS takes place in different forms, contexts or situations. Based on a literature review, we identified three main forms of learning: (1) instruction (e.g., in traditional training sessions), (2) individual (self-learning), and (3) social interaction. First, instruction has been found to be an important source for learning (Boudreau and Seligman 2005) and users seek instructions when they want to learn how to use an IS (Beaudry and Pinsonneault 2005). Instruction is the “delivery of information
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and activities that facilitate learners’ attainment of intended, specific learning goals” (Smith and Ragan 1993, p. 2) by a teacher or trainer with an expert level of knowledge about the system. In general, organizations offer their employees training programs before a new ES is implemented to prepare them for using the new system in their day-to-day tasks (e.g., Sharma and Yetton 2007; Venkatesh 1999). Typically, trainers explain the system to novice users in classroom settings, instruct them how to use its features and answer questions that may arise (Yi and Davis 2003). Therefore, for most users, training represents the first opportunity to learn about the features of a new ES and as a result, it will affect their beliefs and attitudes towards it (Xia and Lee 2000).

Formal instructor-led approaches include classroom-style training sessions (Sykes 2015), remote instruction using multimedia technologies (Lim et al. 2007) and the provision of printed instructions, such as manuals or documentation (Sasidharan et al. 2012). However, researchers point out that even the best training programs cannot anticipate all complexities of actual on-the-job use because opportunities for learning are limited (Sasidharan et al. 2012; Sykes 2015). These limitations result, for example, from rigid training cases which focus on step-by-step instruction and hinder individual exploration of the system (Lauterbach et al. 2014). Second, users learn independently to improve their knowledge of an IS (Barki et al. 2007) to use it more effectively. In this individual context, users experiment with a new system (Maruping and Magni 2012; Spitler 2005; Tennant et al. 2015; Yamauchi and Swanson 2010), explore previously unused features (Ke et al. 2012; Liang et al. 2015), or read about a system’s functionalities in provided manuals (Bagayogo et al. 2014; Spitler 2005). IS research also highlights the importance of learning-by-doing, that is, users learn from experience by using the system to work on their specific tasks (Ryu et al. 2005; Torkzadeh et al. 2011). Third, learning how to effectively use an IS also occurs in the context of social interaction (Sasidharan et al. 2012; Spitler 2005). Social interaction unfolds through interpersonal ties between employees which may be embodied by communication, advisory, or supervisory relationships (Nan 2011). Nan (2011) defines social learning as the “mental activity of perceiving, evaluating, and adopting the more productive practices of others in the workplace” (p. 520). If users experience problems during the usage of an IS, they frequently rely on their social network to get help (Bruque et al. 2008). Typically, users ask more knowledgeable peers for support (Sykes et al. 2009) or contact the help desk or IT staff (Saeed and Abdinnour 2013). Sykes (2015) stresses the advantages of peer support over support from IT specialists because peers possess better work domain knowledge. Researchers have observed that users freely share their knowledge (e.g., how to use a particular functionality) within their team without any formal instruction (Wagner and Newell 2007). Thus, users constantly learn from others by observing their peers and adopting their work practices which enable them to use the system more effectively.

It is an important difference between these three forms of learning that instruction is typically provided as a structured and formal activity to stimulate learning, while learning in an individual context and via social interaction mostly occur in an unstructured and unplanned way based on a “need to know” basis (Boudreau 2003). As mentioned, instruction typically takes place before go-live of a new system, whereas users engage in individual learning or ask peers for assistance when they are actually using the system in the post-adoptive phase. Hence, users often receive instructions in training before they actually have to deal with a new system and new processes on a daily basis, implying a temporal separation (Sykes 2015).

**Learning subject:** In the context of IS, learning processes often involve different learning subjects (i.e., what is learned). Learning how to effectively use a system can be achieved through learning three key subjects: the system’s structures (i.e., surface or deep structure), its representations, and its domain (Burton-Jones and Grange 2013). Boudreau and Robey (2005) observe that ERP system users have learned the surface structure because they know which buttons to push but struggle with its deep structure and rely on shadow systems for complex tasks. Lauterbach et al. (2014) describe how users learn the meaning of representations of an ES to be able to work with it. Domain knowledge is another import subject of learning because it helps users to navigate and use a system effectively (Sykes et al. 2009). Moreover, users can learn the business processes which are defined by the organization and embedded in an ES (Robey et al. 2002). ESs represent the state of business processes (Liang et al. 2015) and through learning these processes, users can better understand how the system is meant to support them in carrying out their tasks.

**Factors influencing learning:** Several factors influence a user’s learning behavior and significantly impact the learning success: (1) technical, (2) individual (i.e., user), and (3) organizational. Technical factors, such as IS’ complexity, affect how users perceive the need to learn a system (Kanter 2000). A user needs to spend more time for learning complex systems as opposed to simple systems (e.g., ES vs. word processor) (Boudreau and Seligman 2005). Moreover, individual characteristics, such as a user’s self-efficacy (Barki et al. 2007), personal innovativeness (Sun 2012), or intrinsic motivation (Ke et al. 2012), have been found to influence the learning process. Additionally, research indicates that demographic factors (e.g., age, gender) can impact the learning...
process (Maruping and Magni 2012). Finally, organizational factors, such as organizational learning climate (Maruping and Magni 2012), influence how individuals engage in learning.

Hypotheses

It is intuitive to expect that learning has a positive effect on EU because users who have learned the system’s structures and how to use it to carry out their tasks can use it more effectively and efficiently in their jobs. However, we argue that it has not been completely clarified when and how users engage in learning to improve their level of EU. We propose that the learning actions suggested by Burton-Jones and Grange (2013) are affected by context-oriented forms of learning. Thus, while the learning actions are concerned with “what” is learned (i.e., the learning subject), the learning forms focus on “how” users learn (i.e., the learning context). To capture the complexity of learning, we develop three constructs: (1) learning via instruction, (2) self-learning, and (3) learning via social interaction. For example, users might learn how to navigate the user interface (i.e., surface structure) through the instructions of a trainer and later, during their experimentation with the system, learn how to leverage its representations to improve their ability to take IAs. As illustrated in Figure 1, our research model integrates the proposed learning constructs into the EU framework and extends the work of Burton-Jones and Grange (2013). In this section, we explain this model and formulate five hypotheses which address the effect of the identified learning forms on three learning actions which in turn influence the EU dimensions. As mentioned before, Burton-Jones and Grange (2013) propose a hierarchical structure for EU in which the lower-level dimension is necessary but not sufficient for the higher-level dimension. To reflect this hierarchy, two relationships have been developed. First, it is suggested that TI directly influences RF since a user naturally needs to interact unimpededly with a system to improve her/his ability to obtain faithful representations. Second, RF has a direct effect on IA as users cannot take IAs without obtaining faithful representations. The learning actions and their relationships with EU dimensions have been developed by Burton-Jones and Grange (2013). Learning the system, which includes learning its physical structure, surface structure and representations, is hypothesized to improve a user’s TI with the system because knowledge of the surface structure (e.g., user interface) will help a user to interact with it. To improve their ability to obtain RF, users need to learn the fidelity of the system’s representations, that is, to learn to assess if a representation faithfully reflects the domain. Thus, learning fidelity is proposed to have a moderating effect on the relationship between TI and RF. Similarly, learning to leverage representations moderates the relationship between RF and IA because users who have learned to leverage a system’s representations will be better positioned to take IAs.

Learning via Instruction

Burton-Jones and Grange (2013) argue that users need to learn the system (i.e., its physical structure, surface structure, and representations) to improve their TI with it. As mentioned before, instruction is concerned with an individual receiving information on how to use a particular system and usually occurs during end-user training. Thus, we define learning via instruction as the extent to which users learn from the instructions delivered by a person with an expert level of knowledge (e.g., trainer or consultant) in a formal setting. Normally, newly hired employees receive a general technology education or already possess knowledge on the underlying physical structure (consisting of computers, keyboards, monitors, etc.). However, instruction also supports the development of general technology knowledge and skills (Gripenberg 2011). Step-by-step instructions help users to become familiar with a system’s user interface (e.g., menus, forms, buttons) and to learn how to navigate it (Lauterbach et al. 2014; Robey et al. 2002). Furthermore, they impart users with basic knowledge on how to do their tasks (Yamauchi and Swanson 2010), which provides an insight into the system’s representations (i.e., the combination of the deep structure and corresponding data). Moreover, organizations often provide additional printed instructions in user manuals or online tutorials (e.g., Saeed and Abdinnour 2013; Sasidharan et al. 2012). Users need basic instructions and a minimum level of IT skills to use the available technology and to get an initial understanding of the system’s functionality (Gao et al. 2014). Moreover, basic functional knowledge is usually sufficient to build confidence among users in their ability to use the system in the future (Gao et al. 2014; Léger et al. 2011). The implementation of a new system is usually accompanied by the introduction of new business processes, which are first explained during training (Robey et al. 2002). This also facilitates the users’ understanding of how the system represents these implemented processes. Thus, we argue that:

H1: Learning via instruction improves a user’s ability to learn the system (i.e., its physical structure, surface structure and representations).
While there is general support in IS literature for the assumption that learning via instruction has a positive effect on learning the system, there is little or no evidence of a significant influence on a user’s ability to learn the fidelity of its representations or how to leverage them. We argue that learning via instruction primarily occurs during formal end-user training. However, researchers have recently suggested more innovative training approaches, such as collaborative technology-mediated training (Gupta and Bostrom 2013) or business simulation training (Léger et al. 2011), which incorporate more than the delivery of instructions by an expert of the system. Gallivan et al. (2005) even suggest that traditional training “may be neither a necessary, nor a sufficient, condition for successful IT usage” (p. 178) because users explore the system on their own or together with their peers. Particularly in integrated applications, such as ESSs, it is important for users to learn how they can effectively coordinate their interactions with other users (Sharma and Yetton 2007). In summary, we argue that through instruction (e.g., in training), users learn the components of a system and how to perform basic tasks, but their level of EU will be rather low as they have not learned RF or how to leverage representations. Thus, we do not hypothesize relations between learning via instruction and the other two learning actions.

Self-Learning

Self-learning includes all activities users undertake to independently learn how to effectively use a system. It has been observed that, users explore a system’s features or additionally provided materials after the roll-out of a new system (Barki et al. 2007; Liang et al. 2015; Spitler 2005). Moreover, users experiment with unknown features (Spitler 2005; Tennant et al. 2015; Yamauchi and Swanson 2010) or discover new ways of exploiting the system by trial and error (Beaudry and Pinsonneault 2005). While users carry out their work and gain valuable experience in using the system, they also engage in learning-by-doing (Ryu et al. 2005; Torkzadeh et al. 2011). The benefits of experiential learning (Kolb 1984) are widely recognized in psychology. Thus, we define self-learning as the extent to which users learn from their own efforts. Burton-Jones and Grange (2013) postulate that users need to learn the fidelity of the system’s representations which is facilitated by learning its representations and domain. We argue that a significant amount of learning takes place when users engage in self-learning. When users use a system in their day-to-day tasks, experiment with it or explore new features, they gain valuable experience. Not only do these activities help them to improve their knowledge on representations and domain, they also foster an understanding of the business logic implemented as the system’s deep structure. Particularly, learning fidelity is difficult without applying the system to actual business problems because training cases cannot replace actual work experience (Lauterbacher et al. 2014; Sasidharan et al. 2012). On-
job usage, however, provides experience of how the system reacts in real life business situations and which typical problems or errors can occur. This helps users to determine if a particular representation faithfully reflects the domain (e.g., if a customer’s phone number in a CRM system is the correct one for this customer). Therefore, we propose that:

\( H_{2a} \): Self-learning improves a user’s ability to learn fidelity towards representations.

Burton-Jones and Grange (2013) further point out that learning to leverage representations will raise a user’s level of EU by improving the ability to take IA. We hypothesize that self-learning significantly contributes to learning to leverage representations because the experience gained through on-the-job usage (i.e., learning-by-doing) or experimentation with a system enables users to make better decisions. Moreover, researchers have found that self-learning activities, such as exploration, increase the use of a system in terms of breadth and depth (Liang et al. 2015; Liu et al. 2011). Even though breadth and depth of use do not imply EU, we argue that when a user has explored new or previously unknown functions, s/he can establish a better foundation for taking IA by leveraging what s/he has learned through exploring the system. Furthermore, users can combine several self-learning activities. For example, a user watches a video tutorial or reads about a feature in the documentation while experimenting with this functionality in the system or performing her/his day-to-day tasks. Thereby, s/he can immediately see the result of her/his actions, understand and react to any problems that may arise and, ultimately, learn new or better ways of doing things in the future. Additionally, users can avoid taking ill-informed actions, which lead to additional effort for correcting errors or poor decisions (Burton-Jones and Grange 2013). In sum, we argue that:

\( H_{2b} \): Self-learning improves a user’s ability to learn to leverage representations.

**Learning via Social Interaction**

Learning via social interaction captures the social embeddedness of learning processes in the workplace. During their work, employees frequently interact with their colleagues and help each other in performing their tasks using the company’s ES (Bruque et al. 2008; Gao et al. 2014; Sasidharan et al. 2012). This provides many opportunities for learning from others (e.g., asking peers for help) and for learning together with others (e.g., collaborative problem solving) (Deng and Chi 2012; Gripenberg 2011). Therefore, we define learning via social interaction as the extent to which users learn from and together with others in the workplace. To improve their ability to obtain RF, users need to learn the domain as well as representations and their fidelity (Burton-Jones and Grange 2013). Sykes (2015) states that peers provide valuable domain knowledge which can lead to a deeper understanding of the system’s domain. Particularly due to the complexity and integration of best practice business processes in ESs, users need more domain knowledge to operate an ES and therefore have to rely on their coworkers’ knowledge (Sykes et al. 2009). Additionally, IT support staff possess general knowledge on the company’s applications (e.g., on its deep structure and representations) (Beaudry and Pinsonneault 2005; Sykes 2015). Furthermore, interaction with peers and support staff also allows users to learn if representations faithfully reflect the domain (Boureau 2003) or to clarify certain system behavior (Yamauchi and Swanson 2010). This timely support not only helps them to successfully complete a task, but may also facilitate determining the faithfulness of a representation in the future. Thus, we argue that:

\( H_{3a} \): Learning via social interaction improves a user’s ability to learn fidelity towards representations.

Burton-Jones and Grange (2013) emphasize that knowledge of how to leverage the obtained representations is necessary to take IAs. We argue that a large amount of this learning occurs via social interaction. According to Nan (2011), employees learn from their top performing peers through social learning. Since EU enhances performance (Burton-Jones and Grange 2013), it seems likely that those colleagues exhibit a high level of EU resulting from their knowledge on how to leverage the system’s representations to take IAs. Employees who still struggle with effectively using the system can learn from these peers by adopting their practices (Nan 2011). Moreover, Lauterbach et al. (2014) observed that users interact with peers or superiors to solve problems in their immediate work performance. “Being able to question a co-located peer in the middle of having trouble” (Yamauchi and Swanson 2010, p. 197) is an effective way to learn how to use the system and to avoid taking ill-informed actions. Thus, we hypothesize that:

\( H_{3b} \): Learning via social interaction improves a user’s ability to learn to leverage representations.
Research Methodology

We investigate the topic under discussion in a longitudinal case study by applying a mixed-method approach (Creswell and Plano Clark 2007), responding to the call for more mixed methods research in IS (Venkatesh et al. 2013). In order to gain a comprehensive understanding of the concept of learning in IS research and to provide a solid foundation for the extension of the theory of EU, we started our research by conducting a systematic literature review (Webster and Watson 2002). Using three online databases, we performed a keyword search in the AIS senior scholars’ basket of journals as well as in the proceedings of the International Conference on Information Systems (ICIS) and the European Conference on Information Systems (ECIS) for the period from 2000 to 2016. Since Marcolin et al. (2000) anticipated the rising attention for richer conceptualizations of use, such as EU, in IS research, we argue that this timeframe includes most relevant literature. The following search query was used: (learn* OR adapt* OR sensemaking OR "sense making" OR "skill acquisition" OR explor* OR train* OR appropriat* OR assimilat*) AND (effect* OR efficien* OR proficien* OR exten* OR enhanced OR sophisticated) AND (use OR usage OR utiliz* OR user). The initial search yielded 1208 results which were filtered in an iterative fashion and resulted in 42 selected articles. The articles were selected according to the following criteria: (1) the article addresses learning or a similar behavior (e.g., sense making) at the individual level and (2) learning occurs in the context of IS use or IS implementation. Following the selection, the articles were analyzed in a “bottom-up” approach as described by Wolfswinkel et al. (2011). First, open coding was applied to the relevant segments of each selected article to derive a set of categories which capture its main concepts. During this coding, 197 codes were created which represent 1782 text segments. Subsequently, axial coding was used to identify interrelations between the identified categories. By aggregating groups of concepts with similar properties, three higher-order categories (i.e., learning context, learning subject and factors influencing learning) and 10 subcategories were created. Finally, through selective coding, the identified categories were integrated and their interrelations refined. The results of the coding process are summarized in Table 1.

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<thead>
<tr>
<th>Category</th>
<th>Subcategory</th>
<th>Exemplary Sources</th>
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<tbody>
<tr>
<td>Learning context</td>
<td>Instruction (e.g., classroom-style training sessions)</td>
<td>(Boudreau and Seligman 2005)</td>
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<td></td>
<td>Individual/Self-learning (e.g., exploration)</td>
<td>(Liang et al. 2015)</td>
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<td>Social interaction (e.g., peer support)</td>
<td>(Sykes et al. 2009)</td>
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<tr>
<td>Learning subject</td>
<td>IS structures (e.g. user interface)</td>
<td>(Boudreau and Robey 2005)</td>
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<td>Representations (e.g., loan contracts)</td>
<td>(Lauterbach et al. 2014)</td>
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<td></td>
<td>Domain</td>
<td>(Burton-Jones and Grange 2013)</td>
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<td></td>
<td>Business processes</td>
<td>(Sasidharan et al. 2012)</td>
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<tr>
<td>Factors influencing learning</td>
<td>Technical (e.g., system complexity)</td>
<td>(Boudreau and Seligman 2005)</td>
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<td></td>
<td>Individual (e.g., self-efficacy)</td>
<td>(Barki et al. 2007)</td>
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<td></td>
<td>Organizational (e.g. learning climate)</td>
<td>(Maruping and Magni 2012)</td>
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Table 1. Coding Framework

Data Collection at Case Organization

Our case organization, a global building materials company with roots in Central Europe, currently performs an ES implementation program in its customer service centers (CSCs) located worldwide. The CSCs are responsible for taking orders for building materials and for distributing these orders to plants and truck drivers. The CSCs were created to optimize the supply chain, reduce operating costs, and improve customer service. In order to standardize heterogeneous IT landscapes and business processes across all CSCs, our case organization implements new hardware (e.g., telephone system), new software (e.g., ERP interface, tools for reporting, etc.), and new business processes (e.g., order intake). The implementation follows a pilot approach in which the system is successively rolled out in different countries. The organization provides training sessions to all involved employees (i.e., agents, dispatchers, supervisors, and managers). A researcher will be on-site at the location of the global IT department to explore the overall implementation program by analyzing documents, attending training sessions, and talking to end-users of the new system as well as the IT staff and managers responsible for the implementation program.
We will conduct a survey of ES users in several locations to empirically test our research model. Data will be collected at different points in time during the implementation process (i.e., after training and after go-live) to examine learning processes in different stages. Due to the complexity of learning, we will not only test the proposed relationships but also for indirect effects (e.g., learning via social interaction → self-learning) and interaction effects (e.g., learning via instruction X self-learning) between the learning forms. A combination of existing and newly developed measures will be used. Learning via instruction is measured by adapting the items for training effectiveness (Bala and Venkatesh 2015) and training satisfaction (Venkatesh et al. 2011). For self-learning, we adapt existing measures for individual adaptation from Barki et al. (2007), as suggested by Burton-Jones and Grange (2013). Learning via social interaction is measured using the construct of social self-regulated learning strategies (Wan et al. 2012). While we have identified existing constructs related to learning actions, such as configurational correctness (Gefen and Ridings 2002) for learning fidelity or performance expectancy (Venkatesh et al. 2003) for learning to leverage representations, they do not fully reflect the conceptualizations by Burton-Jones and Grange (2013). Therefore, we develop our own measures for the proposed learning actions following the recommendations of Burton-Jones and Grange (2013). Since EU and the learning actions have not been empirically tested, we will develop an instrument for their measurement following a standard scale development procedure (Mackenzie et al. 2011). Moreover, the literature review revealed that individual differences influence the learning process, particularly during training (Bostrom et al. 1990). Therefore, we will use control variables to measure personal characteristics (big five), demographic characteristics (e.g., age and gender), learning style (Kolb and Kolb 2005), and computer self-efficacy (Compeau and Higgins 1995). Furthermore, technical and organizational factors appear to have an influence on user learning. Thus, we will additionally consider the effect of perceived technology complexity (Bala and Venkatesh 2013) and perceived process complexity (Bala and Venkatesh 2013).

To gather qualitative data, we will combine several sources of evidence (Yin 2014). Primarily, semi-structured interviews with different types of users in different locations and other stakeholders of the implementation project will be conducted. Additionally, we will observe work activities in the CSCs and analyze documents, such as user manuals, training material and process descriptions. Subsequently, these qualitative data sources will be triangulated with the results of the survey of users in the CSCs. We argue that the complex nature of learning in the context of ESs requires a methodology that allows to study this behavior in depth. Through combining quantitative and qualitative methods in a complementary manner (Venkatesh et al. 2013), we will be able to go beyond the statistical significance of the proposed relationships to explore “how” users learn and “why” a particular learning form might be more effective than another in predicting a user’s level of EU.

Conclusion and Expected Contributions

To examine the effect of learning on EU, we conducted a thorough literature review and defined three forms of learning which were subsequently incorporated into the theory of EU. Through this, we extend the nomological net of EU by integrating the effect of these learning constructs. However, a limitation of our research results from the fact that the scope of our research model is limited to ESs. The context of our study only allows us to analyze how users learn how to use an ES. We argue that an ES context has particular characteristics (e.g., mandatory use at the workplace, complex systems that integrate data and processes, provision of training) which will influence the learning forms a user engages in. This behavior might differ significantly from learning in voluntary use contexts (e.g., Facebook) or system categories discussed by Burton-Jones and Grange (2013) that do not relate to ESs. As we believe that the learning forms can be generalized for all categories of ISs, we aim to extend our conceptual considerations in the future to be able to provide a model for all types of ISs.

Consistent with prior research (e.g., Gallivan et al. 2005; Sasidaran et al. 2012; Sykes 2015), our research model indicates that instruction (e.g., in traditional training sessions) cannot replace the on-the-job learning experience, particularly in the context of EU. This suggests that organizations should not only provide formal training to support an IS implementation. They also need to stimulate learning after the introduction of the new system. This can be done by giving users enough time to explore and experiment with a new system and by encouraging them to share best-practices with their colleagues. In our future research, we aim to collect data from employees of our case organization to empirically evaluate our research model and to conduct interviews with end-users and key stakeholders of a new ES during the implementation process. We will also test for possible interaction effects between the different learning forms. Moreover, we expect to contribute to research with an evaluated EU model extended by three context-oriented forms of learning.
References


