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IT Feature Use over Time and its Impact on Individual Task Performance

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Abstract

Although anecdotal evidence in organizations and research studies suggest that the functional potential of installed IT applications is underutilized and that most users apply just a narrow band of features, there is still little understanding about the nature and implications of change in IT feature use (ITFU) over time. Drawing on technology capability broadening-deepening and IT skill acquisition literatures, this study investigates how IT use—conceptualized at the IT feature level—evolves over time and how it affects continual and distal task performance during the initial usage of an IT application. The results of two longitudinal panel studies of 330 and 314 IT users show that, when users start using an IT application for task accomplishment, ITFU increases non-linearly over time with diminishing growth rates. At early stages of system use, users predominantly extend their ITFU to become more familiar with the system's feature potential, while, at later stages, when users have increasingly recognized a match between the requirements of a work task and system features, they focus more heavily on leveraging a stable subset of IT features to benefit from task completion. As such, the magnitude in broadening and deepening capabilities in using IT features decreases over time. Moreover, both studies reveal that growth in ITFU has, in and of itself, significant impacts not only on immediate performance perceptions but also on more delayed, objective task performance. Researchers will benefit from the study results by better understanding the dynamics of individual ITFU and their performance implications. Managers striving to encourage users to expand their IT feature repertoire may use the results to conduct experience-based feature upgrades or training programs.

***Keywords**: IT Feature Use, Technology Capability Broadening and Deepening, IT Skill Acquisition, Task Performance, Longitudinal Research, Latent Growth Modeling.*

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1. Introduction

Organizations have made tremendous investments in information technology (IT) over the last decades and are increasingly depending on their installed IT applications to increase operational excellence and sustainable growth (Rai, Patnayakuni, & Seth, 2006). However, existing anecdotal evidence in organizations and research studies suggest that organizations still underutilize the functional potential of the majority of their IT applications. In this regard, Jasperson, Carter, and Zmud (2005) summarize that “users employ quite narrow feature breadths, operate at low levels of feature use, and rarely initiate technology- or task-related extensions of the available features” (p. 525), which suggests that a large potential arising from IT use remains untapped.

While various research studies have been conducted to explain such underutilization, avoidance, and narrow scope of IT usage at various points in time (i.e., at pre- or post-adoption stages of IT use), with much of the emphasis being on IT resistance (e.g., Kim & Kankanhalli, 2009), habitual IT use (e.g., Polites & Karahanna, 2012; Limayem, Hirt, & Cheung, 2007) and inhibitors of IT use (e.g., Cenfetelli & Schwarz, 2011), we have little understanding of the changing patterns and implications of IT use over time. Furthermore, although prior research has examined the use of a variety of technologies, most researchers tend to study IT applications as a black box rather than as a collection of specific feature sets (Jasperson et al., 2005). However, a simple increase in the number of features used may not necessarily correlate linearly with an increase in performance outcomes. Individuals can apply features in nonproductive ways, or they may be overwhelmed by the presence of too many features, which can result in an inability to understand all available feature sets or to apply them effectively in their work. In this regard, different levels of prior experience with an IT application and its features can have important differential effects on the effectiveness of IT feature use (Venkatesh & Davis, 1996). More experienced users usually have a deeper understanding of the IT features’ affordances and, thus, are better equipped to benefit from their experience when performing tasks (Taylor & Todd, 1995). However, while researchers have focused on the relationship between prior experience and IT use at a single point in time, the impact of prior experience on users’ ongoing IT feature use over time has remained largely unexplored.

Taken together, since continued use of an IT application is not a one-shot effort and since it involves users’ ongoing, experience-based interactions with varying IT features over time, examining how IT feature use evolves and how it thereby affects task performance should be of theoretical and practical value. In this study, I address this research gap by examining the following research questions: 1) what is the nature and form of change of IT feature use over time when users start using an IT application for task accomplishment?, 2) how can inter-individual differences in IT feature use be explained through experience?, and 3) how does IT feature use affect immediate and more-delayed task performance evaluations and outcomes?

Understanding how IT feature use evolves over time and how it impacts relevant task performance evaluations and outcomes can inform IT managers about how to diagnose, design, and deliver adequate IT feature upgrade and training programs in order to encourage IT users to harness the full potential of IT feature use. I also offer several research and theoretical contributions. First, the study advances existing post-adoption literature in IS research by focusing on the dynamics of change in IT feature use and its performance implications over time. By extending the concepts of technology capability broadening and deepening from organizational capabilities literature to the individual end user level and conceptually linking them to individual IT skill acquisition, I provide an enhanced theoretical lens to explain shifts in patterns of IT feature use over time, with a particular focus on initial IT use. In doing so, I examine individual IT use behavior both at a feature level and over time and, thus, explain why different users evolve very similar or differing patterns of feature use and, as a result, extract differential value from an IT system to accomplish their tasks. Second, recent research has proposed that IS theories need to go beyond simply examining “technology-as-a-black-box” adoption (Burton-Jones & Straub, 2006). These examinations of feature-centric use posit that technology has levels of use that suggest longitudinal designs consistent with more-sophisticated data analysis techniques (Jasperson et al., 2005). By conducting two independent panel studies using latent growth modeling, my study is among the first to go beyond cross-sectional or two-stage models and provide unique conceptual insights about the dynamics through which evaluations and behavior change as individuals engage in IT feature use. Finally, although many IS researchers have pointed to the important role of time in many IS phenomena (Benbasat & Barki, 2007; Saunders, 2007; Orlikowski & Yates, 2002), little effort has been made to embrace time as a core element in post-adoption models. As such, my study contributes to advance our understanding of how tracking a core IS construct's change over time may help us better comprehend its evolving nature and performance effects in its broader nomological network.

In Section 2, I review previous literature on IT (feature) use. In Section 3, I extend the concepts of technology capability broadening and deepening from organizational literature to the user level to derive specific hypotheses on the nature of change in individual IT feature use and its implications. In Section 4, using two longitudinal surveys including four waves of data collection from samples of 330 and 314 IT users respectively, I test these hypotheses. In Section 5, I conclude the paper by discussing the implications of my findings for future research and practice.

2. Literature Review, Theory, and Hypotheses Development

2.1. Previous Literature on IT Use

The research stream examining the adoption and use of new IT has evolved into one of the richest and most mature research streams in the IS domain (Venkatesh, Morris, Davis, & Davis, 2003). Much of this research has been framed around stage models that represent the decisions and activities associated with adopting and diffusing IT applications (e.g., Kwon & Zmud, 1987). While these stage models typically incorporate three high-level stages (i.e., pre-adoption, adoption, and post-adoption activities) and stress the importance of considering the entire process from pre-adoption to post-adoption activities (Rogers, 1962), the majority of prior research has investigated static, cross-sectional models associated with individuals' pre-adoption activities, the adoption decision, and initial use behaviors. Where research attention does address continuous IT use, such behaviors have mostly been examined in two-stage (e.g., including pre-usage and usage stages) models (e.g., Venkatesh, Thong, Chan, Hu, & Brown, 2011; Bhattacherjee, 2001). Only in rare cases have researchers used real longitudinal designs to understand the theoretical mechanisms underlying continued technology use (e.g., Kim, 2009; Ortiz de Guinea & Webster, 2013). As such, although IT use as key construct in IS research has an implied longitudinal dimension, it is primarily studied at one or two points in time.

Often, researchers also tend to conceptualize and study IT applications as a monolithic black box rather than as a collection of specific IT features. Although finer-grained and richer conceptualizations of IT use have been proposed in the literature, such as deep structure IT usage (Burton-Jones & Straub, 2006), the majority of previous studies have rather used quite lean and coarse-grained conceptualizations, such as duration, frequency, or intensity of use (e.g., Venkatesh, Brown, Maruping, & Bala, 2008; Straub, Limayem, & Karahanna, 1995; Li, Hsieh, & Rai, 2013). Few studies have empirically examined IT use from a feature-centric view, and much of their emphasis has been on cross-sectional designs that found variation in the number of technology features used (e.g., Sun, 2012; Barki, Titah, & Boffo, 2007; Burton-Jones & Straub, 2006; Jasperson et al., 2005; Benlian & Hess, 2011b). To the best of my knowledge, only three studies have used longitudinal designs to understand change in IT feature selection and use over time, and collectively they provide inconclusive empirical findings. Hiltz & Turoff (1981), in their study of an electronic information exchange system, found that the number of features considered "extremely valuable" or "fairly useful" varied with a user's experience in using the application. Kay & Thomas (1995) found that users of a Unix-based text editor adopted an increasing number of commands as their use became more sophisticated and that later-adopted features tended to be more complex and powerful than early-adopted features. In contrast, in a longitudinal case study of engineers that used a recently introduced simulation software application, Leonardi (2013) found that the number of features used declined rapidly and stagnated at a low level over time.

In summary, with rare exceptions, and even in the case of carefully conducted two-stage model studies, the vast majority of studies have primarily treated technology use as a static factor or simple difference score (i.e., measured at one or two points in time) and as a black box (i.e., technology as one monolithic block of functionality). While this research has unquestionably yielded a wealth of knowledge regarding the technology use construct and its attendant antecedents and consequences, the fact remains that basic, yet fundamental premises on time and granularity of IT use underlying this cumulative knowledge have remained relatively unexamined.

2.2. Theoretical Background: Broadening and Deepening IT Feature Use

In developing my arguments on the change of IT feature use over time and its relationship with experience-based antecedents and task performance effects, I draw on the key notions of technology capability broadening and deepening from the organizational capabilities literature and extend them to the individual level of analysis (i.e., to end users).

Initially introduced by Argyres (1996) to show how they—as two ways of a firm's technological diversification strategy—can affect interdivisional coordination in multidivisional firms over time, both broadening and deepening technological capabilities have been widely applied in strategic management (e.g., Chen, Yang, & Lin, 2013; Leiponen & Helfat, 2010) and organizational literature (e.g., Ahuja, Lampert, & Tandon, 2013; Kapoor, 2013; Toh & Kim, 2012). As a common underlying theme in this body of literature, companies—especially in situations of high technological uncertainty—face a core trade-off that is related to their technological specialization; that is, firms must determine the extent to which they use and advance their existing stock of technologies versus spreading their technological focus. In this regard, broadening technological capabilities refers to expanding a firm's technological focus by acquiring, learning, and developing new capabilities that help the firm open up new product and market opportunities and hedge risks against technological uncertainty. On the other hand, deepening technological capabilities refers to improving how efficiently they use their existing technologies to increase their immediate return on investment and competitive advantage. Both technological diversification strategies have been found to have their upsides and downsides (e.g., Clark & Huckman, 2012; Leiponen & Helfat, 2010). However, the prevailing consensus in the literature is that balancing both technological capabilities over time rather than relying on just one of these capabilities enables firms to prosper and survive (Lavie, Kang, & Rosenkopf, 2011; March, 1991).

As I note above, the organizational capabilities literature views technology broadening and deepening at the firm level of analysis. However, to develop an understanding of IT feature use that emphasizes the learning cycles individual users go through over time, we need to adapt organizational technology capabilities to the individual level and focus on end users' technology-leveraging capabilities. As such, similar to studies that extended organizational-level theories on dynamic capabilities to the group level (Pavlou & El Sawy, 2006; Pavlou & El Sawy, 2010), I extend the concepts of technology broadening and deepening to the individual level by conceptualizing technology capabilities as individual IT feature capabilities.

Consistent with previous IT skill acquisition literature (Munro, Huff, Marcolin, & Compeau, 1997; Huff, Munro, & Marcolin, 1992; Eschenbrenner & Nah, 2014) that incorporates notions of IT user competences that have close parallels with the concepts of technology capability broadening and deepening, I argue that individuals build up capabilities about information systems and their features over time by increasing the breadth and depth of their knowledge and skills. When users broaden their technology capabilities, they engage in the sense-making of a broad and diverse set of IT features and, thus, extend the scope and variety of IT features they can apply for task completion (Griffith, 1999). In this regard, technology broadening draws on the concept of shallow learning in which users try to broaden their surface knowledge and skills with regard to a system's set of features without going too much into detail. Thus, the main goal of technology capability broadening is to obtain a broad grasp of a system's functionality while actively extending the basket of IT features that may be used by a particular user to accomplish tasks (Huff et al., 1992; Sun, 2012). As an example, a word-processing system user who masters basic editing functionality would broaden their knowledge and skills by exploring and experimenting with new and hitherto unknown features such as spell-checking or referencing.

In contrast, when users deepen their technology capabilities, they try to increase their mastery of already-known features and functionalities. Thus, the depth of a user's knowledge and skills relates to the completeness of the user's current capabilities (Munro et al., 1997). Furthermore, technology capability deepening builds on the concept of deep learning—a mode of learning in which users focus on selected subsets of features in a given basket of IT features to fully grasp the features' affordances, effects, and their associations with already-known IT features (Burton-Jones & Straub, 2006; Sun, 2012). Users thereby improve their existing knowledge through the application of pre-established procedures, technologies, and solutions. Staying with the word-processing system example, a user honing their skills in automatically cross-referencing between different parts of a document (e.g., by using field codes for a table of contents) would deepen their existing IT feature skills and develop more time-efficient work practices.

In this study, I argue that—akin to firms balancing technology broadening and deepening capabilities to achieve desired performance outcomes in uncertain market environments—users broaden and deepen their capabilities in IT feature use over time to adjust their behaviors to the time-varying affordances of their task environments. In this regard, I conceptualize capability-broadening and capability-deepening IT feature use as two complementary patterns of IT feature extensions that reflect users' dynamics in IT feature use. As people initially use a new system or are exposed to new task demands, they usually go through multiple adaptation cycles during which they actively revise their capabilities in using IT features in order to achieve a better fit between the system and the context in which they are using it (Sun, 2012). They create and recreate the system's structure, and this process of creation and recreation may lead to changes in their feature use behaviors over time because it is the specific features in use at any point in time that influence work outcomes (DeSanctis & Poole, 1994; Goodhue, 1995).

While users may always experience a tension between technology capability broadening and deepening activities when using IT features, their overall emphasis may vary over time (Marcolin, Compeau, Munro, & Huff, 2000). When the system and its features are, for example, new to users, they may first focus on extending their capabilities (i.e., by both broadening and deepening their knowledge and skills) to familiarize themselves with the systems' overall functionalities (Bagayogo, Lapointe, & Bassellier, 2014). After a while, however, when users have gained initial experience with the IT features and task performance is prevalent, the need to benefit from leveraging a stable subset of IT features will gain in importance (Burton-Jones & Straub, 2006). In this respect, the distinction between capability-broadening and capability-deepening patterns of IT feature use may have considerable appeal because it can help understand how IT feature use evolves over time and explain why it may affect individual performance evaluations and outcomes. More specifically, it may suggest potentially important differences in the magnitude of change in IT feature use in earlier and later usage periods.

2.3. Research Model and Hypotheses Development

In this section, I develop the hypotheses for my research model shown in Figure 1. This research model sheds light on: 1) the nature and interplay of change trajectories in IT feature use (H1-H2), 2) experience-based sources of inter-individual differences in IT feature use (H3-H4), and 3) potential implications on continual performance evaluations and distal performance outcomes (H5-H6). The scope of this model is the initial IT use phase after installation, which researchers have suggested to be the most critical phase of an IT implementation (Bala & Venkatesh, 2013). Furthermore, it focuses on rather mandatory use contexts in which IT applications are used to support task accomplishment.

2.3.1. The Nature of Change in IT Feature Use

Using a technology application after its installation is not a one-shot effort; it involves one's ongoing interactions with changing structures of IT features in use over time. In early phases after installing a new IT application, users usually start expanding their knowledge and skills about the application's IT features. They not only experiment and tinker with new and unknown features to get a broad grasp of IT feature's purposes and affordances (Munro et al., 1997; Tyre & Orlikowski, 1994), but they also try to improve and hone their skills in using specific IT features to get a more in-depth understanding of the features' performance potentials (Huff et al., 1992). At this early stage of IT feature use, when users still exert more conscious effort for a variety of sense-making and problem-solving activities, the magnitude in both broadening and deepening IT feature use is likely to increase.

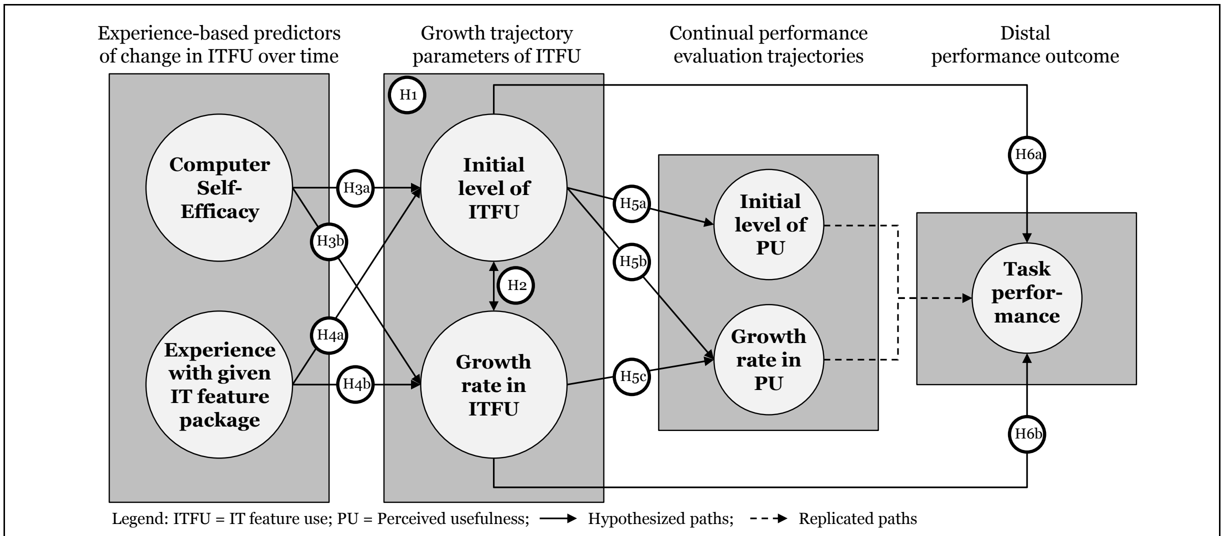


Figure 1. Research Model

At later stages, after an individual has begun to consciously learn about and use the application and its IT features, awareness of the existence, nature, and potential performance implications of the application's features arise and, over time, are fleshed out (Jasperson et al., 2005). Although users may still look for unused features or improve their mastery of already-used IT features at these later stages, they predominantly try to leverage their existing capabilities based on a relatively stable subset of IT features (Huff et al., 1992). As such, IT feature use at later stages can typically be described as efficiency oriented and variety reducing wherein users spend increasingly less time on skill-broadening and skill-deepening activities (Marcolin et al., 2000; Ortiz de Guinea & Webster, 2013). As an individual applies IT features more routinely for a given work task, the ever-accumulating prior-use experiences imprint and reinforce these use behaviors in the cognitive scripts that direct the individual in task accomplishment (Ortiz de Guinea & Markus, 2009; Louis & Sutton, 1991). Accordingly, over time, much post-adoptive IT feature use behaviors become habitualized where the decision to use the IT application feature occurs more or less automatically via a subconscious response to a work situation unless interventions occur to disrupt the formation of these non-reflective mental scripts (Limayem et al., 2007; Ortiz de Guinea & Webster, 2013). As such, IT feature use, over time, likely transitions to a state of habitual behavior in which technology usage increasingly converges towards a recurring pattern of leveraging just a stable subset of features for task accomplishment (Jasperson et al., 2005) so that capability-broadening and capability-deepening patterns of IT feature use gradually decrease over time. Taking early and later stages of IT feature use into consideration, I hypothesize that:

> **H1:** *IT feature use will increase over time with diminishing growth rates.*

Users that have used no or just a limited set of IT features of a newly installed application in the past have, by definition, still more IT features to explore and deficits in mastering these features (Munro et al., 1997). Since marginal benefits from broadening and deepening their IT feature capabilities are typically greater for them (i.e., especially in early phases of their IT feature use) compared to users with higher initial levels of IT feature use, the probability that they will extend their IT feature use and expand their technology capabilities more quickly over time is greater. Conversely, given that individuals leveraging an extended set of IT features right after installing an application (e.g., learned from similar applications or applications of older versions) have less marginal potentials in broadening and deepening their IT feature skills and are also comparatively more used to exploit a stable subset of IT features, the growth in their IT feature use behavior will be relatively lower over time. Accordingly, I hypothesize that:

> **H2:** *Individuals with lower initial IT feature use will exhibit a faster growth in IT feature use than individuals with higher initial IT feature use.*

2.3.2. Experience-based Sources of Change in IT Feature Use

Prior experience has been found to be an important determinant of behavior (Venkatesh & Davis, 1996). Specifically, researchers have suggested that knowledge gained from past behavior will help shape intentions and behaviors regarding future actions (Ajzen & Fishbein, 1980). Given that experience with using an IT application accrues over time and thus triggers path-dependent episodes of use behaviors, I argue that experience is a particularly relevant predictor of IT feature use over time (Jasperson et al., 2005).

Consistent with previous consumer research (e.g., Alba & Hutchinson, 1987) that distinguishes between experience manifested in emerging capabilities (also called *expertise*) and experience gained by accumulating knowledge related to a focal object (also referred to as familiarity), I focus on two different dimensions of experience; namely, computer self-efficacy and experience with the used IT system. Computer self-efficacy (CSE), logically and theoretically derived from Bandura's broader concept of self-efficacy (Bandura, 1976), is "an individual's perception of efficacy in performing specific computer-related tasks within the domain of general computing" (Marakas, Yi, & Johnson, 1998, p. 128). While initially more general CSE measures have been developed to capture perceptions of computer self-efficacy at the computing-behavior level, application domain-specific CSE conceptualizations (e.g., Windows, word processing, and spreadsheet analysis) have been proposed in more recent research (Marakas et al., 2007). Direct experience in a given domain (i.e., in my study with a given IT system) has been studied in several previous IS studies as an important factor affecting individuals' perceptions and subsequent behaviors (e.g., Venkatesh & Davis, 1996; Taylor & Todd, 1995).

I argue that the two experience-based factors will both affect the growth trajectories of IT feature use; that is (1) initial IT feature use and (2) growth rates in IT feature use. First, research studies have found that self-efficacy perceptions are predicted to be a significant precursor to IT use. This hypothesis is supported by research regarding computer use (Burkhardt & Brass, 1990; Compeau & Higgins, 1995). In line with this evidence, I suggest that users with higher application-specific CSE will have higher initial levels of IT feature use right after installing the IT application because users can already draw on previous beliefs about their own capabilities with using the IT application and its features, which reduces behavioral uncertainty. Likewise, I argue that users after direct previous experience with an IT system can make subsequent judgments based on more concrete criteria because they have already broadened their technology capabilities in previous cycles of use (Venkatesh & Davis, 1996). Right after installing an application, both types of experience thus allow "experienced" users to quickly remember and leverage their pre-existing capabilities in using IT features. As such, users with more expertise and familiarity with an IT system will start out with higher initial IT feature use compared to less-experienced individuals (Huff et al., 1992). Thus, I hypothesize that:

> **H3a:** *Individuals with higher application-specific computer self-efficacy will engage in higher initial IT feature use than those with lower application-specific computer self-efficacy.*

> **H4a:** *Individuals with more prior experience with the used IT feature package will engage in higher initial IT feature use than those with less prior experience.*

Second, I argue that CSE and previous experience with a given IT system will also affect growth rates in IT feature use over time. With higher levels of application-specific CSE and more direct experience with the IT system in the past, individuals become increasingly adept in their usage practices, but, at the same time, also more constrained toward a stable subset of IT features. This is because, as individuals gain experience and skills, they tend toward increasingly habitual modes of operation, so that patterns of use congeal over time and users become less open-minded to broadening their technology capability (Ortiz de Guinea & Webster, 2013; Tyre & Orlikowski, 1994). Because such habitual modes of behavior determine which environmental cues are noticed and the manner in which information about them is disseminated, growing experience may lead users to increasingly overlook or ignore new environmental cues (e.g., new IT features). Research suggests that people's arousal, attention, and motivation to engage in effortful problem solving is not constant over time (Ortiz de Guinea & Markus, 2009). More specifically, when users become increasingly routinized in using IT features for a given task and thus leverage their existing skills and knowledge (i.e., less-reflective mental scripts), active thinking and conscious cognitive processing tend to drop sharply over time (Louis & Sutton, 1991). Accordingly, I argue that users with higher application-specific CSE and more prior experience with a given IT system will increasingly rely on a stable subset of IT features over time and thus have lower growth rates in IT feature use than users with lower CSE and less prior experience. Thus, I hypothesize that:

> **H3b:** *Individuals with higher application-specific computer self-efficacy will have lower growth rates in IT feature use than those with lower application-specific computer self-efficacy.*

> **H4b:** *Individuals with more prior experience with the used IT feature package will have lower growth rates in IT feature use than those with less prior experience.*

2.3.3. Continual and Distal Performance Implications of IT Feature Use

The main focus of previous IT adoption and use research that has been strongly influenced by the technology acceptance model (Davis, 1989; Venkatesh & Davis, 2000) and the unified theory of acceptance and use of technology (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012) has been on the antecedents of IT use at the pre-adoption stage. Despite these valuable and established research efforts, few studies have examined the performance effects that may arise from IT use over time in post-adoption stages (e.g., Ortiz de Guinea & Webster, 2013; Kim, 2009; Kim & Malhotra, 2005). However, researchers have shown that. in this stage, when experiences with using information systems accumulate and performance feedback loops increasingly regulate individual behaviors, recursive and reciprocal effect mechanisms—other than the traditional and static pre-adoption perspective of linear effect paths (i.e., from performance evaluations to IT use)—are much better in explaining IT use and their performance implications over time (e.g., Kim, 2009; Bhattacherjee & Premkumar, 2004; Bajaj & Nidumolu, 1998). Following this logic, the behavioral dynamics in post-adoptive IT use become an increasingly important determinant for explaining users' subsequent IT perceptions and individual task performance (Benbasat & Barki, 2007).

Kim and Malhotra (2005), for example, conceptualize the impact of past IT use on subsequent performance evaluations as a "feedback mechanism" that regularly updates users' performance evaluations based on usage information (the "behavior–evaluation relationship"). This feedback mechanism is theoretically grounded in self-perception theory according to which "individuals come to 'know' their own attitudes, emotions, and other internal states partially by inferring them from observations of their own overt behavior and/or the circumstances in which this behavior occurs" (Bem, 1972, p. 2). In this regard, individuals often do not deliberately assess the pros and cons related to the outcome of their actions, but instead tend to infer their performance evaluations—through self-perception processing—directly from past behavior. More specifically, to infer their evaluations, people tend to recall previous incidents of technology use for a certain period of time. Then, these recalled incidents from prior use episodes serve as a basis for forming current judgments. Similarly, Beaudry & Pinsonneault (2005) found that users, when using an IT system, go through multiple adaptation cycles via feedback loops: they learn through trial and error, and the performance outcome of one usage sequence often results in a new sequence. In this regard, the outcome of a usage cycle is evaluated (e.g., through evaluations of the system's usefulness or ease of use) and, if necessary (e.g., if the outcome is not up to the person's expectations), may trigger another usage cycle through the feedback mechanism (Jasperson et al., 2005).

In the context of this study[1], I explicitly focus on two types of performance feedback from IT feature use over time that can be distinguished based on feedback immediacy: 1) continual performance evaluations and 2) distal task performance outcomes. While continual performance feedback reflects proximal, subjective performance evaluations by users during task completion, distal task performance outcomes refer to an objective performance feedback after task completion (Kim, 2009; Burton-Jones & Straub, 2006). Using these two types in tandem allows one to not only capture a more balanced picture of the performance effects of IT feature use, but also more properly account for transitory and lingering effects over time.

From a continual performance feedback perspective, I argue that, right after an application's installation, users with higher initial levels of IT feature use will have higher initial beliefs of perceived usefulness, which is the degree to which individuals believe that using the system will help them increase task performance (Davis, 1989). Having an extended range of IT features tried and tested in the past, they have already experienced how those IT features can be leveraged to support their work activities. In other words, rather than having to further extend their IT feature skills for the sake of learning and experimenting, users with higher initial levels of IT feature use have already increasingly recognized a match between the requirements of a work task and an application's features and, thus, are in a better position to use IT features for positive performance gains (Goodhue, 1995; Goodhue & Thompson, 1995). Thus, consistent with previous research and with feedback mechanisms emerging from IT usage over time, I suggest that initial levels of perceived usefulness will be positively affected by initial levels of IT feature use.

However, as I discuss above, since users with higher initial levels of IT feature use will have lower marginal benefits from extending their skills in IT feature use (simply because they are increasingly constrained to a narrow band of IT features over time due to the habitualization of system use), they will experience a lower increase (i.e., growth rate) in perceived usefulness over time compared to users with lower initial levels of IT feature use (Jasperson et al., 2005). In a similar vein, I argue that users who have higher growth rates in IT feature use over time and thus learn faster by extending their individual IT feature repertoire will experience higher growth rates in perceived usefulness because users draw higher marginal benefits out of IT feature use when they are capable of extending their IT features in use at a higher rate over time (Kim, 2009). Thus, I hypothesize that:

> **H5a:** *Individuals with higher initial IT feature use will experience higher initial perceived usefulness than individuals with lower initial IT feature use.*

> **H5b:** *Individuals with lower initial IT feature use will experience a faster increase in perceived usefulness than individuals with higher initial IT feature use.*

> **H5c:** *Individuals with higher growth rates in IT feature use will experience a faster increase in perceived usefulness than individuals with lower growth rates in IT feature use.*

From a distal performance feedback perspective, I suggest that growth trajectories in IT feature use will also affect more delayed, objective performance outcomes. Since users with higher initial levels of IT feature use have access to a broader and deeper assortment of capabilities, I expect that they can

[1] While the majority of previous research has studied perceived usefulness as an antecedent of IT use with a cross-sectional lens, I deliberately focus on the feedback loops that emanate from IT use over time to impact perceived usefulness (e.g., Kim, 2009; Beaudry & Pinsonneault, 2005). I do this because I argue that IT feature use continuously triggers feedback loops in the form of usefulness perceptions of IT features that may help users decide which IT features should be kept in their behavioral repertoire and which should be discarded. More broadly, I want to better understand IT feature use's continual performance effects with perceived usefulness being one crucial subjective performance evaluation criterion. The precedence of IT feature use to users' evaluations of an IT system's perceived usefulness in each usage period was also a key design criterion of my longitudinal panel studies (Mitchell & James, 2001).

also more effectively leverage these initial capabilities over an extended period of time and that their task performance will consequently be higher at the end of task completion (Yi & Davis, 2003). Burton-Jones & Straub (2006), for example, have shown in a longitudinal study of students accomplishing spreadsheet-based business analysis assignments that deep structure IT feature use is a strong predictor of end-of-semester task performance. In contrast, and as I note earlier, individuals with lower initial levels of IT feature use are less able to tap into an existing reservoir of capabilities that they can leverage for completing tasks in the future. As such, I predict that they will exhibit lower distal task performance.

Along the same lines, I expect that individuals with faster capability-broadening and capability-deepening patterns of IT feature use will exhibit stronger individual task performance. Given that users with higher growth rates in IT feature use learn faster and thus become more skillful in a shorter period of time, it is easier for these users to free up attention and energy from conscious and self-reflective IT feature usage and use these released cognitive resources for problem-solving strategies pertaining to task fulfillment (Louis & Sutton, 1991). At the same time, since users with higher growth rates in IT feature use are likely to be faster in making sense of IT features and thus have more time to exercise with these features at a task, I argue that their task performance will also be higher due to practice effects (Newell & Rosenbloom, 1981). Thus, I hypothesize that:

> **H6a:** *Individuals with higher initial IT feature use will exhibit higher distal task performance than individuals with lower initial IT feature use.*

> **H6b:** *Individuals with higher growth rates in IT feature use will exhibit higher distal task performance than individuals with lower growth rates in IT feature use.*

Several studies in the pre- and post-adoption IT usage literature have theorized and shown that users' performance evaluations of an information system (such as perceived usefulness or perceived ease of use) or of their own capabilities in using this information system (such as software self-efficacy) have direct effects on their task performance (e.g., Yi & Davis, 2003; Goodhue & Thompson, 1995; Goodhue, 1995). Given my primary goal to better understand the antecedents, nature, and performance effects of IT feature use over time, I do not explicitly hypothesize the relationship between continual performance evaluations and distal task performance, but rather replicate it in my research model.

3. Research Methodology

3.1. Sample and Data Collection

Following the data collection design features that Singer & Willett (2003) recommend, I conducted two independent longitudinal studies with different types of IT systems (i.e., first study: word processing systems; second study: business process modeling systems) for two main reasons. First, different types of IT systems allowed me to control my results for robustness across different sets of IT features with varying application content (i.e., word processing vs. process modeling) and context (i.e., private vs. business). Second, since I assumed that study participants would have, on average, higher initial experience with word processing systems than with BPM systems, testing the research hypotheses in two application settings helped me compare my findings across varying initial levels of system experience.

The first study took place between October 2011 and February 2012, and the second study between April and July 2013. In both studies, I used data from four repeated observations during a semester on a group of undergraduate students enrolled in an introductory management information systems (MIS) course (first study) and an introductory business process modeling (BPM) course (second study) at a large public university in Germany. I administered the first wave of each study's data collection at the start of the semester, and evenly spaced out subsequent waves on a monthly basis over the course of the semester (from time 1 [T1] to time 4 [T4]). Every four weeks in the course, I asked the students to submit homework including questions about different course topics (i.e., first study: ERP and CRM systems, Internet, or social networks; second study: business process modeling). In the first study, I instructed each student to use a word processing system to answer the questions, and randomly assigned each student to one of three types of word processing systems[2]: 1) Google Docs, 2) LibreOffice, or 3) MS Word (Benlian, 2011; Benlian & Hess, 2011a). Similar to the first study, I randomly assigned the students in the second study to one of three types of business process modeling systems to complete their homework: 1) Signavio Process Editor, 2) Bonita Open Solution, or 3) ARIS Express. I kept the task type and task difficulty of the assignments constant across all four time points in both studies.

At each wave of data collection, I administered the students with a link to an online survey with questions pertaining to using and evaluating the IT system they will use (T1) / had used (T2-T4) for their homework. More specifically, the online questionnaires included measures of application-specific computer self-efficacy and previous experience with the randomly assigned IT feature packages (T1), IT feature use (T1-T4), and perceived usefulness (T1-T4). I coded the questionnaires to be able to send reminder emails and also to match respondents across time. In both studies, the homework including all three submissions (submitted at T2, T3 and T4) was graded at the end of the term and aggregated to an overall (objective) task performance score.

Of the 485 students who I contacted at T1 in the first study, 421 responded to the first questionnaire (87%). A total of 381 of the T1 respondents completed questionnaires at T2 (90%), and 356 of the T2 respondents returned their questionnaire at T3 (93%). Finally, 330 out of the 356 individuals (93%) responded to the T4 questionnaire. This final sample of students had an average age of 21.5 years (SD = 2.54) and had studied at the university an average of 2.6 semesters (SD = 1.95) at T1. Among participants, 71.9 percent were men and 28.1 percent were women. While the first group (Google Docs; N = 109) indicated that they had the lowest level of experience with their assigned word processing system (mean = 1.55; SD = 1.30), the second (LibreOffice, N = 109; mean = 2.92; SD = 1.71) and third (MS Word, N = 112; mean = 5.17; SD = 1.53) reported relatively higher levels of experience. In the second study, student attrition showed a similar pattern over time (T1: N = 412; T2: N = 372; T3: N = 345; T4: N = 314). Students in the final sample of the second study had an average age of 22.3 years (SD = 2.01) and had studied at the university an average of 2.8 semesters (SD = 2.05) at T1. While both the first and second groups indicated at the beginning of the semester that they had very low experience with their assigned BPM system (Signavio: N = 104, mean = 1.75, SD = 0.56; Bonita: N = 104, mean = 1.42, SD=0.43), the third group (ARIS: N = 106; mean = 2.25; SD = 1.11) had slightly higher levels of experience.

To determine whether attrition produced any detectable outlying responses or demographic differences in the usable samples of both studies, I conducted several analyses following the procedures described in Bentein, Vandenberghe, Vandenberg, and Stinglhamber (2005) and Bollen & Curran (2005). All of these analyses revealed that respondent attrition in both studies did not appear to create any sort of bias along the primary variables.

3.2. Measures

Because I conducted both studies in a German-speaking context, all measures (see Tables 1 and 2 in the Appendix) were translated from English to German by one translator and then back-translated independently by a second translator. Minor discrepancies among translated versions were observed but were resolved by a short discussion between the translators. Except for task performance, which was allocated a single percentage score reflecting students' performance in their homework, and experience with the given IT feature package (PTYPE), which was measured on a seven-point scale ranging from 1 (low experience) to 7 (high experience), I assessed all items with a Likert scale anchored by 1 (strongly disagree) and 7 (strongly agree).

[2] I assumed that students had different initial levels of experience with these three types of word processing systems. This helped us further analyze what role previous experience with a software package plays in influencing IT feature use over time. Furthermore, I could control for the robustness of my findings across different types of software delivery (i.e., (1) on-demand, (2) open-source, (3) proprietary, on-premise).

I borrowed the way I formulated measures for IT feature use (ITFU) from Burton-Jones & Straub (2006). However, content-wise, I drew on Marakas et al. (2007) (first study) and Yu & Wright (1997) (second study) to measure IT features in as comprehensive a way as possible. I selected the IT features based on the premise that they cover a mid-range of task specificity to ask about the class of features used. This balanced the need for comprehensiveness with the need for focused questions (Jasperson et al., 2005; Burton-Jones & Straub, 2006).

I measured word-processing computer self-efficacy (WCSE) with items developed by Marakas et al. (2007). I developed the construct of business process modeling computer self-efficacy (BPCSE) based on business process modeling literature (Ko, Lee, & Lee, 2009; Yu & Wright, 1997) and Marakas, Johnson, and Clay's (2007) guidelines to develop application-specific computer self-efficacy constructs. I measured perceived usefulness (PU) as a construct for subjective task performance using three items adapted from Davis (1989). Consistent with Burton & Jones (2006), I measured individual task performance as an objective assessment of individual task output in terms of its effectiveness; that is, the degree to which it meets specific task goals (and not system-specific output quality standards). In both studies, two independent expert coders (i.e., one faculty member and one PhD student familiar with the course materials) rated task performance using the respective measurement scales, and the interrater reliabilities of both studies were high (first study: ICC(2, 2) = 0.89; second study: ICC(2, 2) = 0.78) (Krippendorff, 2004). Table 1 shows the descriptive statistics of both studies[3].

[3] At every measurement occasion, I assessed the psychometric properties of the measurement models. All of the constructs met the norms and exceeded the thresholds reported in the extant literature (Fornell & Larcker, 1981). For brevity, I omit the detailed computations.

Table 1. Descriptive Statistics of First and Second Studies

	Mean First study (SD)	Mean Second study (SD)	(W/B) CSE	PTYPE	T1-ITFU	T2-ITFU	T3-ITFU	T4-ITFU	T1-PU	T2-PU	T3-PU	T4-PU	TP
(W/B) CSE	4.58 (1.17)	2.23 (0.89)	1	0.42**	0.17*	0.19*	0.25**	0.21**	0.15	0.16	0.18*	0.12	0.25**
PTYPE	3.23 (1.43)	1.81 (0.70)	0.36**	1	0.20**	0.19*	0.26**	0.26**	0.27**	0.23**	0.25**	0.29**	0.30**
T1-ITFU	2.97 (1.08)	1.86 (1.12)	0.15*	0.18*	1	0.79***	0.89***	0.84***	0.39**	0.37**	0.44**	0.45***	0.36**
T2-ITFU	3.97 (1.46)	3.08 (1.50)	0.22*	0.21**	0.88***	1	0.81***	0.80***	0.40**	0.41***	0.46***	0.44***	0.35**
T3-ITFU	4.66 (1.10)	4.07 (1.05)	0.23**	0.23**	0.77***	0.85***	1	0.77***	0.35**	0.41**	0.37**	0.41**	0.38**
T4-ITFU	5.09 (0.80)	4.55 (0.77)	0.24**	0.22**	0.68***	0.79***	0.89***	1	0.37**	0.39**	0.42**	0.45***	0.34**
T1-PU	3.04 (1.21)	2.14 (1.22)	0.07	0.25**	0.42**	0.45**	0.38	0.35**	1	0.60***	0.59***	0.64***	0.66***
T2-PU	3.89 (1.23)	3.21 (1.25)	0.11	0.27**	0.44**	0.47**	0.40**	0.40**	0.67***	1	0.65	0.73***	0.62***
T3-PU	4.45 (1.20)	3.91 (1.28)	0.13*	0.23**	0.41**	0.43**	0.42**	0.41**	0.63***	0.87***	1	0.82***	0.59***
T4-PU	4.76 (1.19)	4.45 (1.19)	0.09	0.27**	0.42**	0.43**	0.43**	0.47**	0.55***	0.79***	0.85***	1	0.66***
TP	78.03 (14.67)	68.25 (10.34)	0.22**	0.29**	0.31**	0.34**	0.37**	0.38**	0.56***	0.61***	0.62***	0.65***	1

Note: WCSE = word processing computer self-efficacy; BPCSE = business process modeling computer self-efficacy; PTYPE = experience with package type; T1–T4 indicate the measurement occasion; ITFU = IT feature use; PU = perceived usefulness; TP = task performance; Correlation matrix of first study and second study is depicted below and above the diagonal, respectively.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

3.3. Data Analysis

I used LISREL 8.8, a widely used covariance-based structural equation modeling tool, to conduct my data analysis, which included tests for measurement invariance and a multiple-indicator[4] latent growth modeling (LGM) analysis (Chan, 1998). I applied the LGM procedure to test my research hypotheses because it has recently gained widespread acceptance as powerful approach for describing, measuring, and analyzing longitudinal change (Zheng, Pavlou, & Gu, 2014; Serva, Kher, & Laurenceau, 2011; Duncan, Duncan, & Strycker, 2006). LGM, which operates in the structural equation modeling framework, integrates the intercepts and slopes of focal constructs to capture individuals' initial status (intercept) on the constructs (at the first time point) and to develop a trajectory of change (slope) for each individual across time. Each individual has their own intercept and slope, and considerable inter-individual variation is expected in both the intercept and the slope. Thus, as for the observed measures, the change trajectories have means and variances, and there is a covariance between the two that help uncover individual differences across the sample and relationships between initial levels and change rates of focal constructs. In sum, unlike traditional techniques that are not able to capture intra-individual change, such as *t*-tests, ANOVA, lagged regression, and difference scores, LGM offers precise information on intra-individual change patterns over time.

[4] I conducted a multiple-indicator LGM (MLGM) to test the hypotheses including multiple indicators for PU and ITFU at each point of time (Bollen & Curran, 2005).

Measurement invariance tests are a prerequisite to LGM to provide evidence that the same construct is being measured across time and measured with the same precision (Ployhart & Vandenberg, 2010). Invariance within a LGM context is said to exist if: a) the nature of the construct that is operationalized by measured variables remains unchanged across measurement occasions (i.e., configural invariance) and b) the relations between measures and their corresponding constructs are invariant across measurement occasions (i.e., metric invariance). Using longitudinal mean and covariance structures analysis (Chan, 1998), both forms of invariance were strongly supported for IT feature use and PU in both of the studies[5].

Consistent with previous studies, LGM analyses in both studies proceeded in three phases (Duncan et al., 2006). I performed a univariate, unconditional LGM analysis in phase one to determine the basic form of the growth trajectory for ITFU. To establish the final model that most adequately depicted the change trajectory, I fitted a series of nested uni-variate LGM models to the data. During phase two of the LGM analysis, I tested a multi-variate, conditional LGM model to assess relationships between potential experience-based predictors and the initial status and slope of ITFU. Finally, I specified an augmented multivariate LGM model in phase three to estimate structural relationships between the growth trajectories of ITFU and PU (i.e., continual performance evaluations) and between the growth trajectories of ITFU and end-of-semester TP (i.e., distal performance outcome).

In this way, analyzing the initial levels and change trajectories of ITFU and their relationships with continual and distal performance outcomes allowed me to assess users' breadth and depth in their ITFU and how the change in ITFU—as manifested in capability-broadening and capability-deepening patterns of IT feature extensions—affected immediate (i.e., continual) and delayed (i.e., distal) individual task performance.

4. Results

4.1. IT Feature Use over Time

To determine the nature of the trajectory of ITFU and whether a no-growth, linear, or free-form model[6] represented the best fit in the study, I compared nested models using chi-square difference tests. The chi-square difference test is implemented by calculating the significance level for the difference in model chi-square values and the degrees of freedom for a pair of nested models (see Table 2).

Table 2. Fit Statistics for Unconditional LGM for IT Feature Use (ITFU)

	First study: word processing systems			Second study: BPM systems		
	No-growth model	**Linear model**	**Free-form model**	**No-growth model**	**Linear model**	**Free-form model**
Chi-square/d.f. (p-value)	26.331 (0.367)	7.973 (0.164)	2.180 (<0.001)	37.130 (0.451)	8.596 (0.182)	2.27 (<0.001)
RMSEA	0.354	0.146	0.020	0.452	0.113	0.040
SRMR	0.155	0.021	0.009	0.187	0.046	0.010
CFI	0.918	0.982	0.998	0.870	0.962	0.992

[5] More specifically, I found strong support for equality of factor loadings and error variances of the first-order factors across time in both of the studies (Chan, 1998).

[6] As Bollen & Curran, (2005) recommend, I used constant factor loadings for the no-growth model, linearly increasing loadings for the linear model (i.e., $\lambda_1 = 1$; $\lambda_2 = 2$; $\lambda_3 = 3$; $\lambda_4 = 4$), and set the factor loadings for the free-form model by fixing $\lambda_1 = 0$ and $\lambda_4 = 1$, while freely estimating all of the loadings between the first and last time points.

Fit statistics for the no-growth models in both studies were quite poor, while those for the linear model were better but not satisfactory. However, the free-form models provided an adequate fit to changes in ITFU. The chi-square difference tests between the no-growth and the linear model (first study: $\Delta\chi^2$ (3) = 18.36; p<0.001; second study: $\Delta\chi^2$ (3) = 20.36; p<0.001) indicated a better fit of the linear models. The chi-square differences between the linear and free-form models were also significant (first study: $\Delta\chi^2$ (2) = 5.793; p<0.01; second study: $\Delta\chi^2$ (2) = 6.572; p<0.01), which indicates that the free-form models provided a better fit to changes in ITFU in the two independent samples. The results for the estimated factor loadings of the free-form models (first study: $\lambda_1 = 0.00$, $\lambda_2 = 0.47$, $\lambda_3 = 0.80$, $\lambda_4 = 1.00$; second study: $\lambda_1 = 0.00$, $\lambda_2 = 0.58$, $\lambda_3 = 0.89$, $\lambda_4 = 1.00$) allowed me to interpret the differences between successive factor loadings as cumulative proportion of change between time points relative to the total change occurring from the first to the last time points (Bollen & Curran, 2005). For example, $\lambda_2 = 0.47$ reflects that 47 percent of the total observed change in ITFU occurred between the first two waves. Similarly, $\lambda_3 = 0.80$ reflects that 80 percent of the total observed change in ITFU occurred between the first and third assessments; and $\lambda_3 - \lambda_2 = 0.33$ reflects that 33 percent of the total change occurred between the second and third wave.

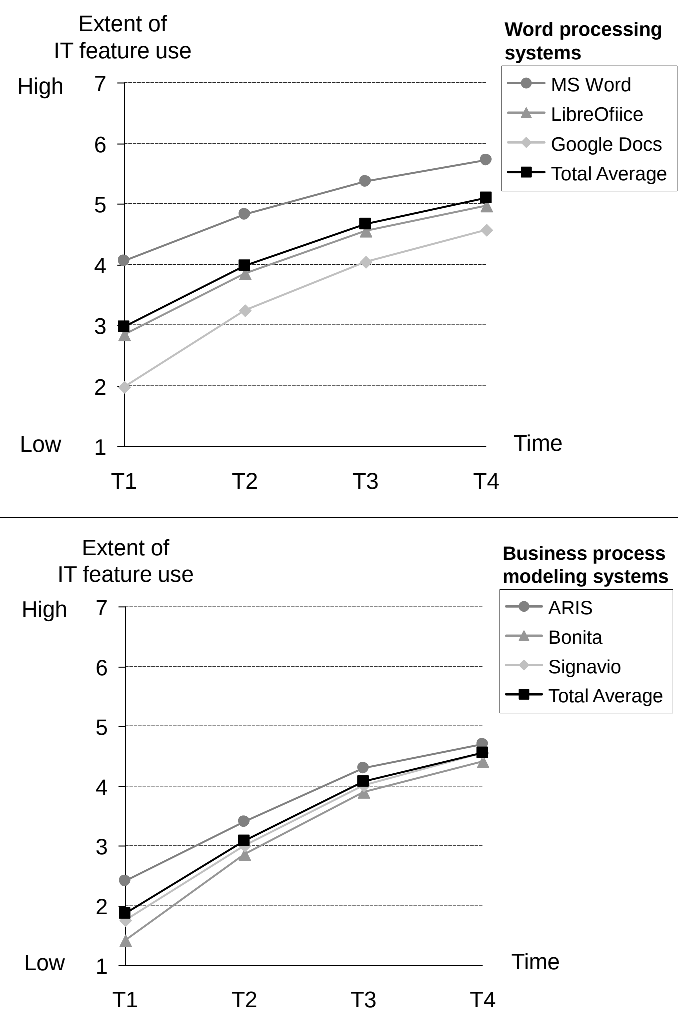
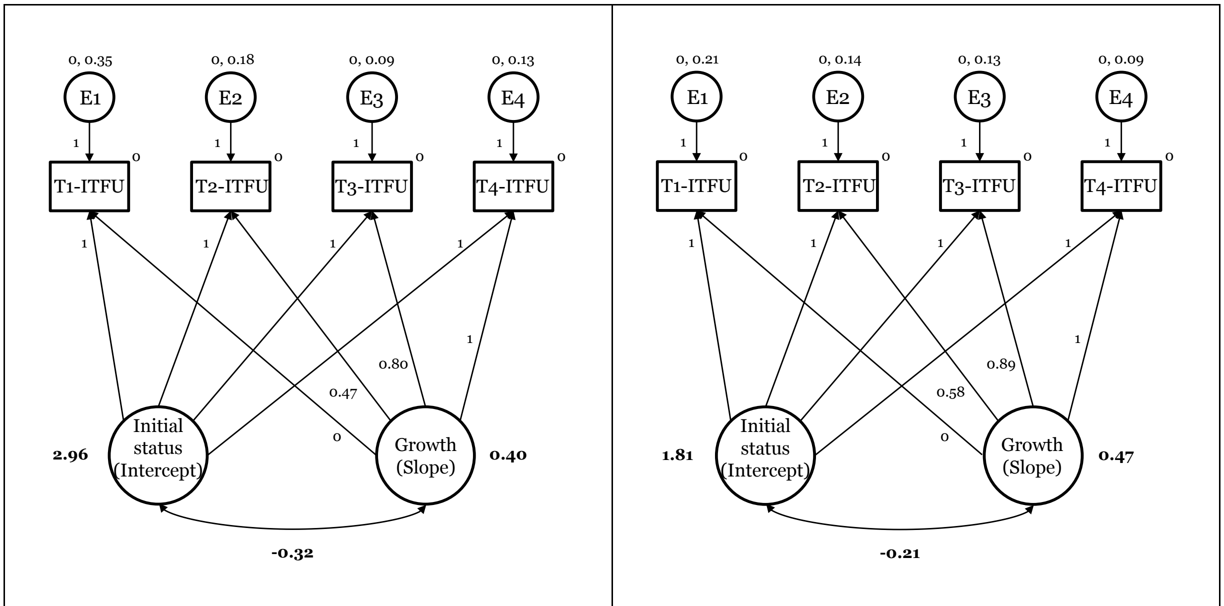


Figure 2. Growth Trajectory of IT Feature Use; First Study (Top), Second Study (Bottom)

As such, the results in both studies indicate a nonlinear trend in ITFU over time with diminishing growth rates, which supports H1. This conclusion is supported by the plots of average ITFU (see Figure 2) for both studies that show that ITFU increased with diminishing growth rates over the semester, regardless of initial experience with and the type of software package used. In addition, the increasingly lower standard deviations (after T2) and the lower marginal increases in the means for ITFU across the four time points (see Table 1) indicate that this nonlinear trend is reflected in diminishing capability-broadening and capability-deepening patterns of IT feature use. Furthermore, the extent of ITFU of students with different initial levels of experience converged over time. While there was a substantial gap in ITFU between groups using different software packages at the beginning of the courses (i.e., in particular for the first study), the gap grew significantly smaller over time.



Study 1: Word processing systems	Study 2: BPM systems

Figure 3. Unconditional Free-Form Models

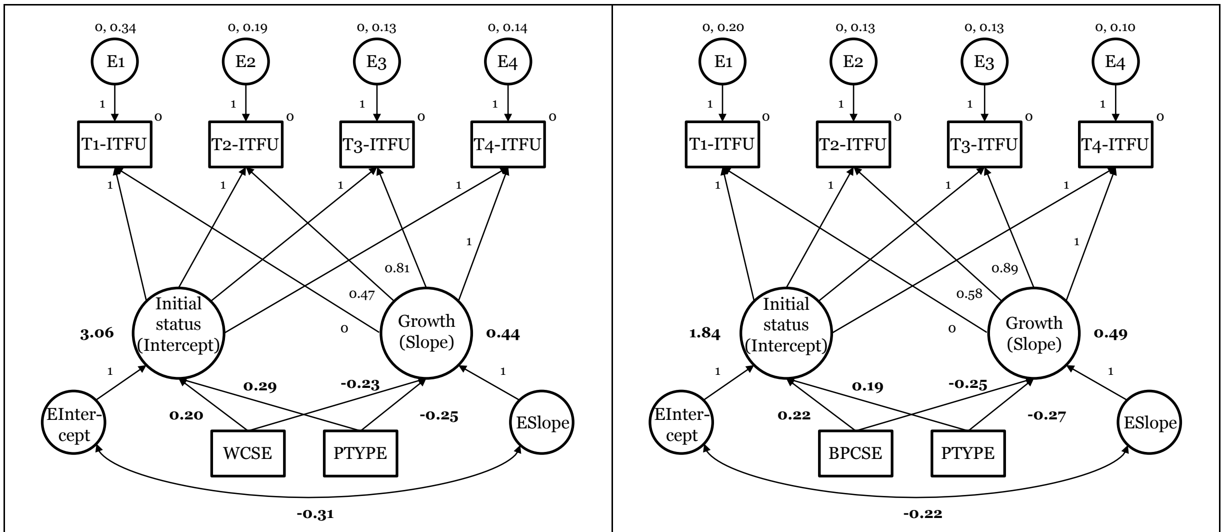
Analyzing the presence of significant inter-individual differences in starting point and slope for changes in ITFU, I examined the trajectory values of the free-form models (see the unconditional free-form models for both studies 2 in Figure 3). The intercepts were 2.96 (first study) and 1.81 (second study), and the corresponding z-scores were both significant, indicating that, on average, students' ITFU levels started out greater than zero. The slope values of 0.40 and 0.47 indicate a significant (i.e., both $p<0.001$) increase in ITFU in each time period. The variances for the intercept and slope of both studies were also significant (i.e., both $p<0.001$) indicating that students' growth trajectories exhibited significant individual differences across the samples (i.e., they differed from the mean initial ITFU level and the mean ITFU growth rate). The covariances between the intercepts and slopes were negative (first study: -0.32; second study: -0.21) and significant (i.e., both $p<0.01$), indicating that students with high initial levels of ITFU experienced lower growth rates (i.e., slopes) in ITFU over time and vice versa, which supports H2.

4.2. Experience-Based Predictors of Change

Given the significant inter-individual differences in the intercepts and slopes for change trajectories in ITFU, I next introduced WCSE (first study) / BPCSE (second study) and PTYPE as potential predictors into the LGMs that we hypothesized would explain the inter-individual differences (see the conditional models for change in ITFU in Figure 4).

The conditional models of both studies showed good fit (first study: $\chi^2/df = 2.78$, $p<0.001$, CFI = 0.980, RMSEA = 0.048 and SRMR = 0.030; second study: $\chi^2/df = 2.91$, $p<0.001$, CFI = 0.972, RMSEA =

0.052 and SRMR = 0.032). Paths from WCSE/BPCSE and PTYPE to the two growth constructs were significant in both studies, indicating that ITFU initial levels (first study: $\beta_{WCSE} = 0.20$, $p<0.05$; $\beta_{PTYPE} = 0.29$, $p<0.01$; second study: $\beta_{WCSE} = 0.22$, $p<0.01$; $\beta_{PTYPE} = 0.19$, $p<0.05$) and rate of change (first study: $\beta_{WCSE} = -0.23$, $p<0.01$; $\beta_{PTYPE} = -0.25$, $p<0.01$; second study: $\beta_{WCSE} = -0.25$, $p<0.01$; $\beta_{PTYPE} = -0.27$, $p<0.01$) differed across WCSE/BPCSE and PTYPE. As such, individuals with higher CSE and with more experience with the used IT feature package started the course with higher ITFU levels, but had significantly lower growth rates than individuals with lower CSE and with less experience. These results indicate that individuals with higher CSE and more previous experience with an IT feature package were able to make use of and leverage more IT features at the outset of the semester, while individuals with lower CSE and less experience with an IT feature bundle learned faster to increase their repertoire of used IT features over time, which supports H3a, H3b, H4a, and H4b.



First study: word processing systems	Second study: BPM systems

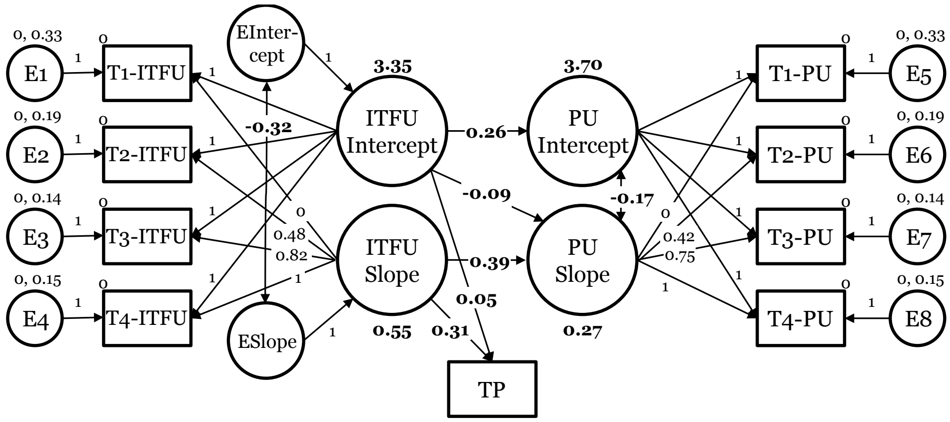
Figure 4. Conditional Models with WCSE and PTYPE as Predictors

4.3. ITFU’s Impact on Continual and Distal Performance Outcomes

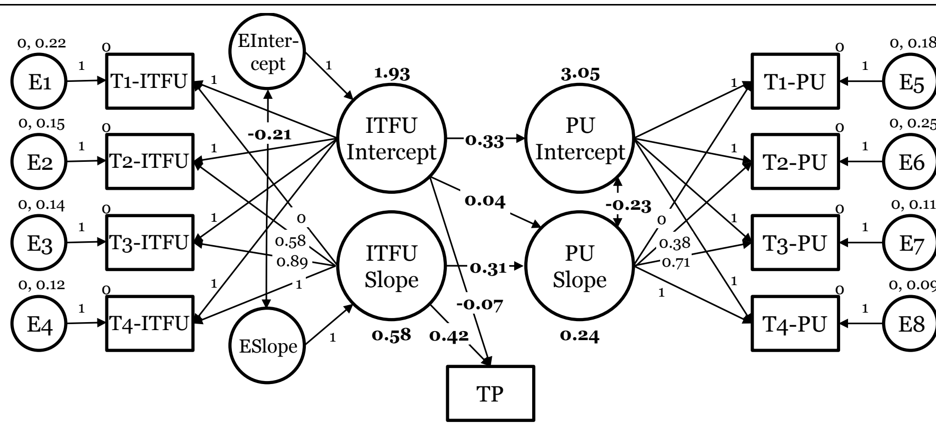
The fit statistics for the dual growth models (i.e., models that link growth in two different focal variables simultaneously, here ITFU and PU) of both studies were fairly good (see Figure 5) (first study: χ^2/d.f. = 1.62, $p<0.001$, CFI = 0.995, RMSEA = 0.024, and SRMR = 0.027; second study: χ^2/d.f. = 1.79, $p<0.001$, CFI = 0.983, RMSEA = 0.039, and SRMR = 0.030)[7]. The means for the intercepts and slopes of free-form growth (with diminishing returns) in PU were statistically significant (first study: mean intercept = 3.70, $p<0.001$, mean slope = 0.27, $p<0.001$; second study: mean intercept = 3.50, $p<0.001$, mean slope = 0.24, $p<0.001$), suggesting that students’ PU grew non-linearly over the semester, similar to ITFU’s growth over time[8].

[7] For the sake of clarity and because their impact on ITFU growth trajectories remained significant, I omit WCSE and PTYPE from this dual growth model.

[8] I also estimated no-growth and linear models for PU in both studies. However, the models with the best fit statistics were the free-form models with diminishing growth rates (first study: $\lambda_1 = 0.00$, $\lambda_2 = 0.42$, $\lambda_3 = 0.75$, $\lambda_4 = 1.00$; second study: $\lambda_1 = 0.00$, $\lambda_2 = 0.38$, $\lambda_3 = 0.71$, $\lambda_4 = 1.00$).



First study: word processing systems



Second study: BPM systems

Figure 5. Dual Growth LGMs with PU and TP as Performance Outcomes

Similarly, the variances for PU's growth trajectory parameters were also significant ($p<0.001$ for both studies), suggesting that they were different for each individual. The covariance between the intercepts and slopes was negative and significant (first study: -0.17, $p<0.05$; second study: -0.23, $p<0.01$), suggesting that students with lower initial PU experienced a faster rate of growth in PU over the semester than students with higher initial PU.

For the dual growth relationships between ITFU and PU, the paths from the intercept of ITFU to the intercept of PU were significant in both studies (first study1: β = 0.26, $p<0.001$; second study: β = 0.33, $p<0.001$), suggesting that students with high initial ITFU experienced higher initial levels of PU. However, although the paths between the slope of ITFU and slope of PU were also positive and significant in both studies (first study: β = 0.39, $p<0.001$; second study: β = 0.31, $p<0.001$), the paths between the initial level of ITFU and slope of PU were not significant (first study: β = -0.09, $p>0.05$; second study: β = 0.04, $p>0.05$), suggesting that growth in PU over time is not dependent on the initial level but on the growth rates of ITFU. As such, these results support H5a and H5c, but reject H5b.

Similarly, I found a mixed picture for the distal outcome variable TP in both studies. While the paths from the intercept of ITFU to TP were not significant (first study: β = 0.05, $p>0.05$; second study: β = -0.07, $p>0.05$), the relationships between the slope of ITFU to TP were significant and positive (first study: β = 0.31, $p<0.001$; second study: β = 0.42, $p<0.001$), suggesting that it is a higher rate of growth in ITFU—and not its initial level—that leads to higher end-of-semester TP[9]. These results support H6b, but reject H6a. Table 3 summarizes the results of the hypotheses tests.

Table 3. Summary of Hypotheses Testing

Hypotheses		First study	Second study
		Supported?	
H1	ITFU will increase over time with diminishing growth rates	Yes	Yes
H2	Individuals with lower initial levels of ITFU will exhibit a faster growth in ITFU than individuals with higher initial ITFU.	Yes	Yes
H3a	Individuals with higher application-specific computer self-efficacy will engage in higher initial ITFU than those with lower application-specific computer self-efficacy.	Yes	Yes
H3b	Individuals with higher application-specific computer self-efficacy will have lower growth rates in ITFU than those with lower application-specific computer self-efficacy.	Yes	Yes
H4a	Individuals with more prior experience with the used IT feature package will engage in higher initial ITFU than those with less prior experience.	Yes	Yes
H4b	Individuals with more prior experience with the used IT feature package will have lower growth rates in ITFU than those with less prior experience.	Yes	Yes
H5a	Individuals with higher initial ITFU will experience higher initial perceived usefulness than individuals with lower initial ITFU.	Yes	Yes
H5b	Individuals with lower initial ITFU will experience a faster increase in perceived usefulness than individuals with higher initial ITFU.	No	No
H5c	Individuals with higher growth rates in ITFU will experience a faster increase in perceived usefulness than individuals with lower growth rates in ITFU.	Yes	Yes
H6a	Individuals with higher initial ITFU will exhibit higher distal task performance than individuals with lower initial ITFU.	No	No
H6b	Individuals with higher growth rates in ITFU will exhibit higher distal task performance than individuals with lower growth rates in ITFU.	Yes	Yes

5. Discussion

In this paper, I advance our understanding about patterns of IT feature use that occur in particular when users start using an IT application for task accomplishment and how those patterns impact critical performance evaluations and outcomes over time. To this end, based on empirical evidence from two independent longitudinal studies of IT users, I 1) explored the temporal patterns of change in IT feature use, 2) examined potential experience-based predictors of inter-individual differences in the change of ITFU, and 3) investigated ITFU's impacts on both continual performance evaluations and distal task performance outcomes. As such, I investigated how and why people change their patterns of IT feature use in the initial post-adoption stage. In addition, I transfer the concepts of technology capability-broadening and capability-deepening from the organizational capabilities literature to individual IT feature use to explain varying magnitudes of users' appropriations of IT features over time. I also examined two experienced-based antecedents to

[9] For replication purposes, I also tested models in both studies that additionally included paths from the growth trajectories of perceived usefulness to individual task performance. The fit statistics remained fairly good (first study: χ^2/d.f. = 1.73, p<0.001, CFI = 0.993, RMSEA = 0.036, and SRMR = 0.033; second study: χ^2/d.f. = 1.85, p<0.001, CFI = 0.971, RMSEA = 0.045, and SRMR = 0.038). Consistent with previous studies (e.g., Yi & Davies 2003), the paths from the initial level to TP (first study: β = 0.34, p<0.001; second study: β = 0.37, p<0.001) and from the slope of PU to TP (first study: β = 0.45, p<0.001; second study: β = 0.49, p<0.001) were positive and significant, confirming that immediate performance evaluations have a strong impact on more delayed task performance.

explain why and under what conditions users change their IT feature use and how such use lead to different performance outcomes over time.

5.1. Main Findings and Implications

The study has three key findings. First, it provides empirical support for a positive and non-linear temporal pattern of ITFU in the initial phase after adoption, regardless of the experience with a concrete IT feature bundle used. After a period with stronger initial increase in ITFU in which there is still a larger potential for discovering new features and for honing existing ITFU capabilities, the growth in ITFU tapers off as increasingly routinized, habitual, and non-reflective IT feature use takes precedence over substantive, reflective behavior. As such, the functional form of ITFU over time that I found in the two studies followed a non-linear dynamic similar to a logarithmic growth function. With increasing ITFU over time, we thus observe diminishing marginal returns, such that growth in ITFU is subject to saturation effects (i.e., the curves tend to flatten out over time), which is typical for path-dependent and self-reinforcing learning behaviors (Gersick, 1991). From these results, we can also infer that growth in ITFU is gradual and persistent rather than disruptive and discontinuous, which is in line with previous studies in the technology-learning and skill-acquisition literature (e.g., Ackerman, Kanfer, & Goff, 1995). While these results are important first steps to analytically grasp and illustrate temporal patterns in ITFU over time, more work is needed to corroborate or complement these findings in different work contexts (e.g., organizational ITFU) and environments (e.g., highly dynamic use environments with frequently changing task requirements vs. stable environments with purely voluntary system use).

Second, the study shows that experience-based predictors can explain inter-individual differences in the change of ITFU over time. Interestingly, although individuals with higher initial application-specific CSE and higher previous experience with the IT feature bundle exhibited higher initial levels of ITFU, they increased their IT feature use more slowly over time than individuals with lower levels of computer self-efficacy and less prior experience. As long as the IT features offered by an IT application are still largely unknown and have to be actively discovered and mastered, users with little previous experience have to devote much attention and energy towards broadening and deepening their capabilities in using the IT features. In such situations, users are much more open to take in and process new information and thus learn new stimuli (e.g., IT features) in their environment. However, as users gain experience, they establish stable routines, norms, and habits for using the technology that decrease the need for active and effortful decision making. This constrains further feature-extension activities and apparently stunts individual capability-broadening and capability-deepening learning processes.

Finally, the study shows that change in ITFU significantly affected both subjective, continual performance evaluations and objective, distal performance outcomes. However, and most interestingly, it is not the initial level (i.e., the pre-existing breadth and depth of capabilities in using IT features) of ITFU but rather the growth in ITFU over time (i.e., the learning speed) that had an impact on these performance criteria. That is, users can improve their task performance in particular through continuously adapting their IT feature capabilities to the given task requirements over time. In contrast, relying on a fixed set of IT features learned in the past does not guarantee high task performance but seems to be rather counterproductive because it hampers users from dynamically adjusting their IT features in use.

As such, based on these findings, we can conclude that expanding IT feature use over time (i.e., by broadening and/or deepening technology capabilities) leads to an increase in perceived usefulness and task performance. However, and similar to the development of ITFU over time, this performance increase is subject to saturation effects, suggesting that the marginal benefits of extending an IT feature set diminishes over time.

5.2. Contributions to Theory and Research

This study makes three main contributions that relate to 1) the dynamics, 2) the granularity, and 3) the performance implications of IT feature use over time. First, this study highlights the significance of understanding the nature of different patterns of IT feature use that are enacted by users over time. As Jasperson et al. (2005, p. 543-544) summarize in their seminal paper on the feature-centric view of technology, “we know little about the patterns of feature adoption, use, and extension that occur throughout the post-adoptive stage of diffusion or the cumulative impacts of those patterns on work system performance over time”. Existing IS research has provided evidence that beliefs related to IT change over time (e.g., Kim & Malhotra, 2005). There is also evidence that employees perceive significant changes in their jobs following an IT implementation (e.g., Bala & Venkatesh, 2013; Lapointe & Rivard, 2005). Until recently, however, little attention has been given to explain the dynamics and changing patterns of IT feature use over time, even though the importance of understanding longitudinal mechanisms of system use has been echoed for decades in the IS literature (e.g., Saunders, 2007; Benbasat & Barki, 2007; Orlikowski & Yates, 2002). By showing that capability-broadening and capability-deepening patterns of IT feature use are employed in different degrees at different stages of initial post-adoptive system use, this study conceptualizes time-varying patterns of IT feature use that advances our understanding of how and why users adjust their capabilities over time to learn and leverage IT features for task completion. Therefore, my findings complement prior findings in the IS post-adoption and IT skill-acquisition literatures that users extend the breadth and depth of their IT feature capabilities at varying degrees over time, which depends on their prior experience and learning speed. Because time plays such a critical role in many IS phenomena (Saunders, 2007), such focus on the dynamics of IT feature use over time may not only open up new lines of inquiry in post-adoptive IT use research, but may also advance our understanding of other inherently longitudinal constructs in IS research such as user resistance (e.g., Kim & Kankanhalli, 2009), IT service quality (e.g., Watson, Pitt, & Kavan, 1998; Benlian, Koufaris, & Hess, 2011), and/or trust (e.g., McKnight, Choudhury, & Kacmar, 2002).

Second, while the IS literature has predominantly focused on a high-level view and on “technology-as-a-black-box” examinations of IT use, I argue that a lower-level and finer-grained conceptualization is also relevant, particularly in longitudinal use settings, because it is the specific features in use at any point in time that determine work outcomes (DeSanctis & Poole, 1994). Responding to calls for richer conceptualizations of IT use (Burton-Jones & Straub, 2006), I developed feature-centric constructs of IT use patterns in order to unblackbox one of the most (if not the most) important phenomena in IS research. Constructs are relevant when they can give insightful explanations to important questions (Barki et al., 2007), and I believe that feature-centric IT use patterns that are enacted over time do so in at least two important ways. On the one hand, the identified expansion and stabilization patterns of IT feature use help us to disentangle how and why specific types of use patterns emerge over time and why other types do not. For example, two people might start using a newly installed information system at the same time for a given task but exhibit different use patterns and task performance because one has managed to expand (i.e., broaden and deepen) their IT feature capabilities faster than the other. That is, it is users’ growth trajectory in IT feature use that helps explain which and why use patterns are enacted. On the other hand, conceptualizing IT use at the feature level allows one to trace the pathways through which users adjust their individual baskets of IT feature use and thereby accomplish tasks more or less efficiently over time. Two different users may, for example, use different sets of IT features or master specific features in different degrees but have the same task performance. As such, a feature-centric conceptualization and operationalization of IT use will help to uncover heterogeneity in the breadth and depth of IT feature use that would go unnoticed in studies examining IT use at the application-system level. Taken together, my findings complement the emphasis on feature-centric IT use in the post-adoption literature (Jasperson et al., 2005), to which they contribute a distinctive and finer-grained conceptualization and operationalization.

Finally, this study complements previous IS post-adoption research by contributing evidence for the empirically underexplored assertion that users employ self-perception processing in the post-adoption stage such that IT feature use influences subjective performance evaluations (i.e., ITFU → PU) through feedback mechanisms (Kim, 2009; Kim & Malhotra, 2005). In particular, and as a distinct finding of this study, I could show that it is not the baseline level but the change (i.e., the growth rate) in IT feature use that has, *in and of itself*, significant impacts on individuals’ continual and distal performance outcomes over time. Consistent with positive conditioning and the law of practice

(Skinner, 1965; Newell & Rosenbloom, 1981), this finding suggests a self-reinforcing learning mechanism that, in turn, suggests that users' performance evaluations of an information system and their own task performance increases as they become increasingly familiar with a system's features and thus more confident and skillful over time. Further, it is this positive performance feedback that spurs users to continue using the system for successful task completion. As such, it is users' marginal progress in improving their IT feature capabilities—and not their experience or capabilities at a single point in time—that has an impact on their performance evaluations and outcomes. My findings therefore also extend the assertion made in the broader organizational capabilities literature (e.g., Jarzabkowski, 2004) to the individual level that it is the ongoing broadening and deepening ("what actors do")—and not the initial breadth and depth ("what actors have")—of technology capabilities that leads to better performance outcomes.

5.3. Limitations and Future Work

Despite this study's contributions in investigating the dynamics and implications of IT feature use in two longitudinal research studies, four salient limitations of the study merit consideration. First, caution should be taken when drawing conclusions from a limited number of studies that focused on IT feature use in the initial IT use phase after system adoption. While I chose to conduct two independent studies in different application settings to increase the robustness of the findings, examining change in IT feature use and its influence on important performance criteria at different post-adoption (e.g., acceptance, routinization or infusion) stages, across several additional types of IT applications (e.g., ERP, CRM or E-Commerce systems), across different levels of analysis (e.g., individual and group levels), and in various institutional (e.g., for-profit and non-for-profit organizations), cultural (e.g., individualistic vs. collectivistic countries and societies), and use (e.g., mandatory vs. voluntary; utilitarian vs. hedonic) contexts would further advance longitudinal research on IT feature use. A second boundary of my research studies is the use of student samples that may limit the generalizability of the findings. Although I consider the use of students subjects to be appropriate because students frequently use information systems, and because I examined basic post-adoptive IT feature use behaviors that should be similar in a more general population of IT users, future research should replicate my studies to examine whether the results hold for subject groups with different demographics and task environments. Third, given that I measured ITFU with a fixed number of IT features, the possibilities I had to measure technology capability broadening (i.e., using more/different IT features over time) was limited. However, I believe that my two studies provide sufficient potential for technology broadening because the students have had low to medium initial experience with the IT applications they used to complete the tasks. Moreover, as recommended in the literature, I selected the measures for the IT features based on the premise that they covered a comprehensive mid-range of task specificity to ask about the class of features used. Nevertheless, investigating technology capability broadening over time based on a finer-grained feature level warrants further research. Finally, although this study is longitudinal, the timeframes I covered in the studies was limited and, thus, insufficient to capture all possible evolutionary paths of IT feature use over time. It is, for example, conceivable that over longer periods of time, IT users forget, ignore, combine, or repurpose IT features that may alter their usage patterns. Thus, future research should not only explore short-term patterns of IT feature use under varying conditions (e.g., stable vs. disruptive), but also mid- to long-term patterns that provide insights into IT feature use across sequences of alternating equilibrium and revolutionary periods.

5.4. Implications for Practice

Practitioners can learn from my study how IT feature use evolves over time and how it impacts IT users' task performance. Based on this knowledge, they may be better able to diagnose possible shortcomings and deficiencies in IT feature use that may be due to a lack of functionality that is customized to specific organizational needs, lack of continual system upgrades and enhancements, or IT users' lack of understanding of existing IT features. As a result, practitioners may be able to design and deliver adequate IT feature customization and upgrade programs and experience-based training interventions on a regular basis to successfully enable users to appropriately enrich their use of already installed IT systems during the post-adoption stage. Based on this study's findings, organizations need to regularly induce interventions that break IT users' habits and automatic responses in IT feature use (Ortiz de Guinea & Markus, 2009), especially given that IT use behavior congeals over time. In this regard, creating a climate for innovation in which users have the perception that change and creativity are encouraged and that they can take risks, tackle problems in new ways, and generally be open to new approaches to solve problems may be a promising approach to attenuate the downsides of congealed and inflexible patterns of IT feature use. Understanding how experienced and non-experienced IT users differ in their IT feature use over time could also inform practitioners about how and when to initiate targeted technology capability broadening and deepening activities and programs in the user community. Such inducements would, for example, give users sufficient time to experiment with IT features and to acquire frequently needed capabilities that would pave the way for periods of efficient work execution, during which users might leverage the learning so gained.

6. Conclusion

Until recently, little attention has been given to patterns of IT feature use over time, even though the importance of change and granularity in IT use has been acknowledged for many years in IS research. This study makes a unique contribution by demonstrating that users change their patterns of use at the feature level over time and that it is this change in the users' IT feature repertoire that affects their individual task performance. I hope that this study will serve as a springboard for future research studies and also aid practitioners in devising experience-based training programs that help users permanently challenge and improve their IT feature capabilities over time.

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Appendix

Table A1. Measurement Scales of First Study (Word Processing Systems)

Constructs	Indicators		Source
IT feature use (ITFU)	When I was using the word processing system, I used features that would help me …		Burton-Jones & Straub (2006), Marakas et al. (2007)
	ITFU1	move a block of text	
	ITFU2	manipulate the way a paragraph looks	
	ITFU3	add a footnote to a document	
	ITFU4	merge information from two documents	
	ITFU5	insert and delete words in a paragraph	
	ITFU6	change the appearance of words or phrases within a paragraph	
	ITFU7	check or improve my grammar in a document	
Word processing computer self-efficacy (WCSE)	I believe I have the ability to …		Marakas et al. (2007)
	WSE1	move a block of text using a word processor	
	WSE2	manipulate the way a paragraph looks using a word processor	
	WSE3	add a footnote to a document using a word processor	
	WSE4	merge information from two documents using a word processor	
	WSE5	insert and delete words in a paragraph using a word processor	
	WSE6	change the appearance of words or phrases within a paragraph using a word processor	
	WSE7	check or improve my grammar in a document using a word processor	
Perceived usefulness (PU; Subjective task perf.)	PU1	Using the word processing system enables me to accomplish my tasks more quickly	Davis (1989)
	PU2	Using the word processing system improves my task performance.	
	PU3	Using the word processing system increases my productivity.	
(Objective) Task performance (TP)	This relatively objective scale allocated a single percentage score based on marks for the following components (The scale was created independently from the research by task experts and was assessed by independent coders):		Adapted from Burton-Jones & Straub (2006)
	TP1	Specifying the problem	
	TP2	Outlining the structure of the solution	
	TP3	Presenting facts and evidence for solutions	
	TP4	Providing references and sources for facts	
	TP5	Synthesizing and highlighting the core aspects of the solution	
	TP6	Giving clear recommendations (i.e., answers to questions)	
	TP7	Creating a focused homework	

Table A2. Measurement Scales of Second Study (Business Process Modeling Systems)

Constructs	Indicators		Source
IT feature use (ITFU)	When I was using the business process modeling system, I used features that would help me …		Burton-Jones & Straub (2006), Ko et al. (2009), Yu & Wright (1997)
	ITFU1	add activities, events, and gateways to my business process model	
	ITFU2	manipulate the way activities, events, and gateways look	
	ITFU3	analyze and assess the performance of my business process model	
	ITFU4	check the syntax of my business process model	
	ITFU5	import and export business process model	
	ITFU6	manage different versions of my business process model	
	ITFU7	generate reports about my business process model	
Business process modeling computer self-efficacy (BPCSE)	I believe I have the ability to …		Ko et al. (2009), Yu & Wright (1997), Marakas et al. (2007)
	WSE1	add activities, events, and gateways to my business process model	
	WSE2	manipulate the way activities, events, and gateways look	
	WSE3	analyze and assess the performance of my business process model	
	WSE4	check the syntax of my business process model	
	WSE5	import and export my business process model	
	WSE6	manage different versions of my business process model	
	WSE7	generate reports about my business process model	
Perceived usefulness (PU; Subjective task perf.)	PU1	Using the business process modeling system enables me to accomplish my tasks more quickly	Davis (1989)
	PU2	Using the business process modeling system improves my task performance.	
	PU3	Using the business process modeling system increases my productivity.	
(Objective) Task performance (TP)	This relatively objective scale allocated a single percentage score based on marks for the following components (The scale was created independently from the research by task experts and was assessed by independent coders):		Adapted from Burton-Jones & Straub (2006)
	TP1	Identifying problems and requirements for the business process	
	TP2	Modeling an adequate representation of the business process	
	TP3	Correctly analyzing the business process model	
	TP4	Identifying levers for business process optimization	
	TP5	Outlining impacts of business process optimization	
	TP6	Giving clear recommendations (i.e., answers to questions)	
	TP7	Creating a focused homework	

About the Author

Alexander BENLIAN is Full Professor of Information Systems and Electronic Services at Darmstadt University of Technology (TU Darmstadt), Germany. He holds a PhD in Business Administration and Management Information Systems from the University of Munich. His main research interests are in the use and value of information technology, business–IT alignment, human-computer interaction, and digital business models. His work has appeared in international journals such as *Journal of Management Information Systems*, *MIS Quarterly Executive*, *Journal of Service Research*, *Information Systems Journal*, *European Journal of Information Systems*, *Journal of Information Technology*, *Decision Support Systems*, *International Journal of Electronic Commerce*, *Electronic Markets*, *Business & Information Systems Engineering*, and several others. He is currently Associate Editor of the *European Journal of Information Systems* and the *International Journal of Electronic Commerce* and serves the Editorial Review Board of the *Journal of Service Research*.