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Usage and impact of technology enabled job learning

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Abstract

Individuals use technology to experiment with new ways of carrying out their tasks and in doing so they learn more about their jobs. The current study examines the role of technology enabled job learning as a key component in the complex relationship between information systems use and technology outcomes. Data from 308 end-users were analyzed to evaluate the relationships between system use and technology enabled job learning, and technology enabled job learning and technology outcomes. Technology enabled job learning was conceptualized in terms of how computer applications helped individuals learn and better perform their jobs. System use was conceptualized in terms of decision support, work integration, and customer service. Technology outcomes were conceptualized in terms of management control, task innovation, task productivity, and customer satisfaction. Results suggest that systems use has a significant, positive effect on job learning, and that job learning has a significant, positive effect on technology outcomes. *Post hoc* analyses were then conducted to examine the potential mediating role of job learning between systems use and technology outcomes. The findings from this research lead to a greater understanding of how patterns of systems use influence organizationally relevant outcomes through technology-enabled job learning.

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Introduction

Although it is widely accepted that information system use should lead to organizationally relevant outcomes, the unanswered question is how. Specifically, how does the pattern of system use (that is, technology application in decision making, problem solving, or customer service) lead to certain outcomes (such as increased productivity, innovation, or customer satisfaction). System use in and of itself does not lead to outcomes; there is instead an expectation that increased cognition and understanding of the task at hand would result in improved outcomes. As individuals interact and experiment with system applications, learning accumulates about a task and productivity is ultimately enhanced (Narayanan *et al.*, 2009). With the opportunity to experiment with different approaches for managing a task, the individual gains knowledge about that task and the process of 'learning to learn' (Schilling *et al.*, 2003) occurs. Task-related experience and learning is expected to have stronger influence on outcomes than specialization (Boh *et al.*, 2007).

Because of this potential to experiment with task management, information technology plays a critical role in the expansion of knowledge; learning becomes a new form of labor (Zuboff, 1988). For the

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individual, information technology holds promise in terms of job enhancement and the outcome of labor. Information technology influences how a job is performed and the expected outcomes. Thus, there is a need for a better understanding of the nature and outcome of the interaction between people and technology in an organizational context.

Despite the importance of technology enabled learning in the relationship between system usage and organizational outcomes, it has received very little theoretical or empirical attention in the information system literature. In this study, we propose that system use enables the individual to learn about their job and that job learning in turn leads to improved outcomes. In other words, technology enabled job learning plays a key role in the relationship between system use and outcomes; task learning becomes a by-product of technology application and technology outcomes become a consequence of task learning. This proposition is important because (a) it helps us to better understand the role of technology enabled job learning as it relates to system usage and outcomes, and (b) it enables organizations to better utilize information technology applications to achieve desired outcomes.

A newly developed measure of technology enabled job learning, as well as previously published measures of systems use and technology outcomes were used to collect data from 308 end-users and to examine the proposed relationships. Measures of technology enabled job learning describe technology influence on the individual's ability to learn and perform job functions and improve work quality. Measures of system use describe patterns of use in terms of decision support, work integration, and customer service. Measures of technology outcomes describe perceived outcomes in terms of management control, task innovation, task productivity, and customer satisfaction. In the following sections we will review the relevant literature, present hypotheses, describe the model and measures, present our findings, and draw conclusions.

Systems use, learning, and technology outcomes

Information technology plays a pivotal role in the structure of work and human productivity. Organizations often attribute their high performance to effective application of information systems. Increasingly, information system executives are required to explain technology expenditures in terms of individual benefits and organizational outcomes. Specifically, organizations are concerned about what technology use means in the context of organizationally relevant outcomes. Because of this, the system success paradigm has progressed from an emphasis on 'suitability for use' where design features such as content, accuracy, format, and ease of use are considered important, to an emphasis on 'benefit of use' where systems' outcomes for the individual and the organization are considered essential (Melone, 1990; Torkzadeh & Doll, 1999). In this section, we review the relevant literature on the three constructs involved in this study.

Technology enabled job learning

Information technology has influenced the nature of work, the process of learning, and ways of accomplishing organizationally relevant tasks. Job learning is an important component of performance in modern organizations. 'Learning is no longer a separate activity that occurs either before one enters the workplace or in remote classroom setting … . Learning is the heart of productive activity' (Zuboff, 1988, p. 395). Although most employers require evidence of capabilities/skills from new hires, a significant part of learning occurs as the work is being performed. Continuous learning forms an important part of the new employment relationships between employer and employee (Weick, 1996). Learning in the workplace has been characterized as the process of seeking technical, referent, and normative information (Morrison, 1993). In a study of salespersons' technology usage, Ahearne *et al.* (2008) reported that increased information technology use enhanced salespersons adaptability and increased performance.

At the individual level, work-based learning occurs when people experiment with new ways of doing things (Lambrecht *et al.*, 2004). At the collective level, work-based learning occurs when people interact with one another and develop shared understandings to perform a task (Raelin, 1997). This categorization is similar to what Lankau & Scandura (2002) have labeled 'personal skill development', defined in terms of acquisition of new skills and abilities, and 'relational job learning', defined in terms of increased understanding about the interdependence or connectedness of one's job to others. Extending work-based learning from the individual to the group, to the entire organisation, is the characteristic of a 'learning organisation'. Implementation of knowledge management systems is one way for organizations to provide and/or enhance work-based learning through application of information technology.

Although there is a long history of information systems use at the workplace, research on how this use affects job learning is very limited. As individuals interact with technology to accomplish tasks, they learn more about their job and become more innovative in carrying out responsibilities (Ruiz-Mercader *et al.*, 2006). Decision support systems and methodologies help organizations understand and reduce the cognitive complexity of tasks (Lilien *et al.*, 2004). The use of information technology is expected to enrich and broaden jobs (Long, 1993). Information technology also enables employees to deliver more value to the customer (Harvey *et al.*, 1993). Employees use information technology in innovative ways to enhance their customer service. Customer relationship management (CRM) systems are a good example of applications that help employees to develop new and innovative ways of providing customer service. Cross-functional integration and effective data processing provided by CRM applications enable employees to access customer profiles and product information and even predict customer needs (Reinartz *et al*., 2004; Torkzadeh *et al*., 2006).

In this study, we define technology enabled job learning as a user's perception of the extent to which an application enhances learning about the job/task performed. As employees use systems for decision support, they are likely to learn more about the decision variables that need to be included for that analysis as well as justification for the decision. By using systems to coordinate and communicate with others, the user would see the benefit of the system for learning about the people and work flow related to the task at hand. The enhancement of job learning through system use should ultimately produce positive outcomes.

Information system research has for some time proposed a link between system usage and individual performance (DeLone & McLean, 1992), but little empirical research has been conducted to examine this relationship (Burton-Jones & Straub, 2006). Researchers have devoted considerable attention to the introduction of new technology and transformation of work practice (Orlikowski & Robey, 1991; Orlikowski, 1996; Winter & Taylor, 1996; Barrett & Walsham, 1999; Robey & Boudreau, 1999; Orlikowski, 2000; Schultze & Boland, 2000; Schultze & Orlikowski, 2004). However, how work practices change with information technology use has not been adequately explored (Vaast & Walsham, 2005). There is a need to better understand the way individuals use applications in their work, the way that technology use helps them learn about their job, and the way technology use influences work practice. That is the focus of this study.

System use

The measurement of information systems success continues to be an important topic for research and practice. At least two perspectives exist in the literature for measuring systems success: the design perspective and the outcome perspective. The design perspective has a strong tradition in the MIS field and involves evaluating systems relative to design specifications or user needs. The outcome perspective calls for performance-related evaluations that focus on outcomes. Measures of user satisfaction (Torkzadeh & Doll, 1998) and perceived usefulness (Davis, 1989) are widely accepted examples of the design perspective. Measures of technology effect on work (Torkzadeh & Doll, 1999) and technology effect on competitive advantage (Sethi & King, 1994) are good examples of the outcome perspective.

Information systems use may influence individuals' performance depending on how the system is used and for what purpose. System use is suggested to influence work performance in one of two ways: exploration or exploitation (March, 1991). System exploration enables the individual to generate new ideas for performing a task. System exploitation enables the individual to make decisions and execute a task. Recent studies have proposed a contextualized model of system use and individual performance based on exploitative usage (Burton-Jones & Straub, 2006). Whether the system enables the individual to 'explore' or 'exploit' work practice, it should lead to better learning of the job. The level of this influence is expected to vary depending on the extent of system use (Venkatesh & Davis, 2000) as well as the cognitive absorption due to system use (Agarwal & Karahanna, 2000).

System use has also been considered as a measure of system success in earlier research (Ein-Dor & Segev, 1978; Ives *et al*., 1980; Hamilton & Chervany, 1981). It is considered to be a key variable in explaining the influence of technology on performance (Devaraj & Kohli, 2003; Ahearne *et al*., 2008). System usage has been viewed as an important construct in conceptualizing information system success (DeLone & McLean, 1992; Torkzadeh & Doll, 1998). However, other studies argue that the critical success factor in technology investment is not system use in and of itself, but the net benefits to organizations that occurs from that use (Szajna, 1993; Seddon, 1997). Therefore, while system use is a pivotal link in the 'system-to-value chain' from technology adoption to social and economic outcome (Doll & Torkzadeh, 1991), it is the outcomes of use that reflect system success. In this taxonomy user satisfaction and perceived usefulness are expected to influence system use. Figure 1 depicts the place and value of technology use in the 'system-to-value chain' and the upstream and downstream research domain.

There is great diversity in the definitions of system use in information system research (Burton-Jones & Straub, 2006). While the emphasis of IS literature on system use is more concerned with the justification for creating and/or utilizing information systems, the social science literature on the nature of work views information technology as being used by individuals in a work context to perform certain organizationally relevant functions (Torkzadeh & Doll, 1998). For example, information technology is used to communicate with subordinates and superiors, to facilitate problem-solving, to plan team work, to service customers, or to rationalize decisions.

In order to measure how information technology is actually used by individuals in an organizational context, Torkzadeh & Doll (1998) developed a multidimensional instrument for technology utilization for the three functions of decision support, work integration, and customer service. The decision support function was defined in terms of 'problem solving' (the extent that information technology is used to analyze cause and effect relationships and to make sense out of data) and 'decision rationalization' (the extent that information technology is used to improve the decision making processes or explain/justify the reasons for decisions). Work integration was defined in terms of 'horizontal integration' (the extent that information technology is

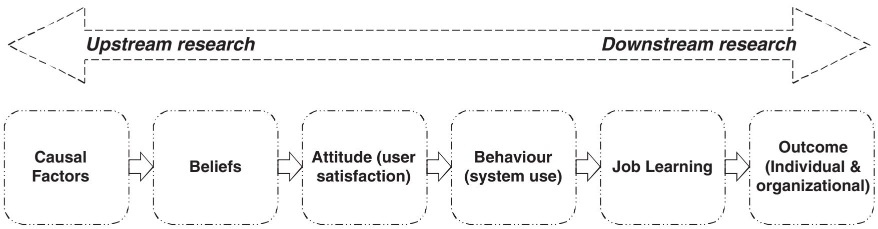

Figure 1 System to value chain.

used to coordinate work activities with others in one's work group) and 'vertical integration' (the extent that information technology is used to plan one's own work, monitor performance, and communicate vertically to coordinate one's work with superiors and subordinates). Customer service was defined as: the extent that information technology is used to service internal and external customers. This empirically supported categorization of system-use is applicable to most information technology tasks (Barki *et al*., 2007). Table 1 provides definitions for the three constructs supported by literature and adopted for the current study.

Information technology use for decision support, work integration, and customer service is expected to influence individual job learning as described above. One would expect some level of cognitive development for the individual who interacts with the system to 'make sense out of data' or 'to justify the reasons for decisions' (Torkzadeh & Doll, 1998). In a study of the relationship between technology use and salesperson performance, Ahearne *et al*. (2008) report a significant effect of information technology use on salespersons' knowledge. They suggest that using the information technology system 'helps salespeople update their knowledge about the market and about their specific products' (p. 682). Their results suggest that learning takes place due to interaction with information technology and that learning is task specific. Other studies suggest that information technology helps reduce the cognitive complexity of tasks (Lilien *et al*., 2004). Thus, based on this discussion, we propose the following relationships between system use and job learning.

H1: *System use measured in terms of decision support is expected to be positively related to job learning.*

H2: *System use measured in terms of work integration is expected to be positively related to job learning.*

H3: *System use measured in terms of customer service is expected to be positively related to job learning.*

Technology outcomes

Organizations are increasingly interested in the extent and nature of their IT investment outcomes, and how application development and acceptance benefits their bottom line. Individual and organizational outcomes of information technology use have been an ongoing topic of research over the years (Brynjolfsson *et al*., 1994; Pinsonneault & Kraemer, 1997; Chan, 2000; Kohli & Devaraj, 2003). Research studies have addressed information technology outcomes from a variety of perspectives including: new ventures (Fairlie, 2006), business performance (Brynjolfsson & Hitt, 2000), competitive advantage (Sethi & King, 1994), organizational strategy (Mahmood & Soon, 1991), time management (Sulek & Marucheck, 1992), industry level (Segars & Grover, 1994), and work transformation (Vaast & Walsham, 2005).

A recent study examined the nature of research on information technology outcomes and reported that the majority of studies reflect a technological imperative perspective followed by organizational imperative and to a lesser extent an emergent perspective (Pare *et al*., 2008). Although this study's review of the research on outcomes was limited to three journals, the findings nevertheless suggest a continuing interest in the topic. While improving the adoption and use of information technology continues to be an important goal of information system executives, there is an increased emphasis on the net benefits that emerge from system use (Seddon, 1997). Information system executives are expected to explain the value and contribution of information technology expenditure in terms of increased productivity, quality, and competitiveness (Myers *et al*., 1997).

Table 1 Definitions of system usage

Construct	*Definition*
Decision support	The extent that information technology is used to analyze causal relationships and to improve the decision making processes or explain/justify the reasons for decisions.
Work integration	The extent that information technology is used to coordinate work activities with others in one's work group, plan one's own work, monitor performance, and communicate and coordinate one's work with superiors and subordinates.
Customer service	The extent that information technology is used to service internal and external customers.

Traditional approaches for measuring technology outcomes emphasize productivity and management control. The extent of information technology use and its influence on productivity and management control has long been the focus of attention (see, for example, Braverman, 1974; Zuboff, 1988; Weick, 1990). MIS researchers have devoted considerable attention to the influence of information technology on productivity (Hirschhorn & Farduhar, 1985; Cooper & Zmud, 1990; Kraemer & Danziger, 1990; Sulek & Marucheck, 1992). More recently, that emphasis has included the influence of technology on innovation and customer service. In addition to productivity and management control, the influence of information technology on innovation and customer satisfaction has also gained increased attention (Curley & Pyburn, 1982; Davis, 1991; Harvey *et al*., 1993; Filiatrault *et al*., 1996). To help management distinguish between effective and ineffective applications, Torkzadeh & Doll (1999) developed a set of outcome measures in the context of management control, task innovation, task productivity, and customer satisfaction. Table 2 provides definitions for these four constructs.

These definitions have specific implications for the current study. First, despite the fact that the measures for these constructs are defined in terms of individual beliefs about technology outcomes relative to a specific task, they are distinct in terms of the outcomes they measure (as evidenced by strong inter-item convergence and reliability). Second, the measures are relevant and useful in an organizational context. Third, because they capture technology outcomes for an individual in the specific context of his or her job duties, they are naturally correlated (as evidenced by inter-factor correlation). This suggests that these four constructs can be grouped for hypothesis development purposes.

The review of the literature presented above provides strong support for the relationship between job learning and technology outcomes (Zuboff, 1988; Weick, 1996; Lambrecht *et al*., 2004; Ruiz-Mercader *et al*., 2006). Whether job learning occurs because the cognitive complexity of work is reduced (Lilien *et al*., 2004), the nature of the job is enriched (Long, 1993), the work situation is better understood (Bereiter, 2002), or experimentation is provided for learning the ropes (Lambrecht *et al*., 2004), job learning is ultimately expected to influence organizational outcomes. Although this literature supports the influence of job learning on technology outcomes, there is a lack of empirical findings regarding the specific dimensions of expected outcomes. The four technology outcome dimensions defined and measured by Torkzadeh & Doll (1999) provide an ideal opportunity to examine the influence of job learning on specific technology outcomes. Therefore we adopt these concepts of technology outcomes in this study, and propose the following hypotheses:

Table 2 Definitions of information technology outcome

Construct	*Definition*
Task productivity	The extent that an application improves the user's output per unit of time.
Task innovation	The extent that an application helps users create and try out new ideas in their work.
Customer satisfaction	The extent that an application helps the user create value for the firm's internal or external customers.
Management control	The extent that the application helps to regulate work processes and performance.

H4: *Job learning is expected to be positively related to information technology outcome in terms of management control.*

H5: *Job learning is expected to be positively related to information technology outcome in terms of task innovation.*

H6: *Job learning is expected to be positively related to information technology outcome in terms of task productivity.*

H7: *Job learning is expected to be positively related to information technology outcome in terms of customer satisfaction.*

Figure 2 depicts the final research model as described by the hypotheses developed above.

Research methods

Operationalization of constructs

To examine the relationships depicted in Figure 2, a combination of newly developed and published measures was used to collect data. Prior to developing measures of perceived technology enabled job learning, we carefully considered whether the construct should be measured reflectively or formatively. The issue of conceptualizing constructs as reflective or formative has received considerable attention in the information system literature in recent years, attention that is quite appropriate given the need to develop valid measures for developing and testing theory within the IS discipline.

There were several factors that led us to develop a reflective measure for technology enabled job learning. It is suggested that the decision to measure constructs using effect (reflective) or casual (formative) indicators should be based upon the research objectives, the substantive theory for the latent construct, and the empirical conditions (Chin, 1998a, b). In the current study, our objective was to account for the observed variances among the indicators, rather than accounting for unobserved variance at the construct level, suggesting that reflective indicators would be superior to formative ones

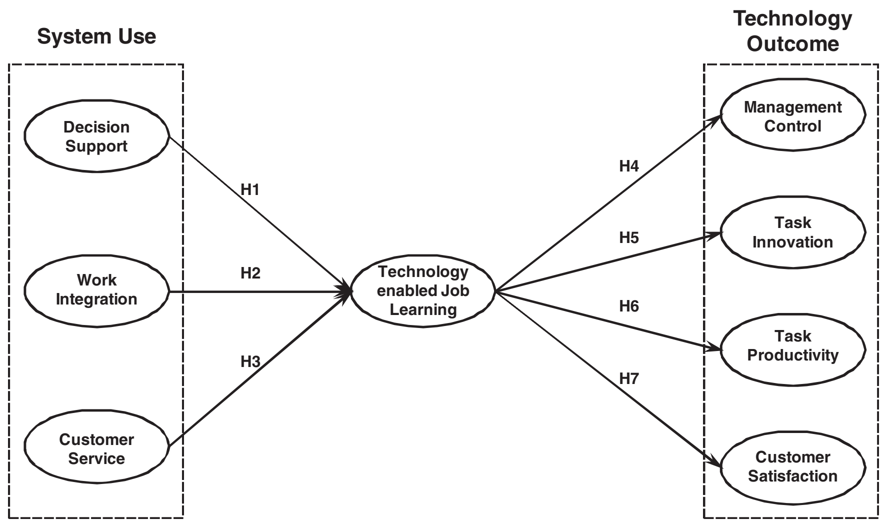

Figure 2 Usage-learning-impact relationship model.

in the present context. In addition, relying on formative indicators would have rendered weights that were dependent on the endogenous variables in the study (Hardin *et al.*, forthcoming), limiting our ability to evaluate the factor structure of the job learning measure independent of its relationship with systems use and technology outcomes, thus limiting the generalizability of the measure to other studies (Howell *et al.*, 2007). While substantive theory on technology enabled job learning is immature, the measure is conceptualized as perceptual, placing it within the realm of psychological constructs suggested as being best measured reflectively (Jarvis *et al.*, 2003). Major concerns with measuring psychological constructs as formative include the inability to completely capture the construct's meaning using perceptual measures and the assumption of error-free measurement at the item level (Diamantopoulos, 2008; Hardin *et al.*, 2008a, b). Formatively measured constructs are defined by their indicators and the omission of an indicator that captures a unique portion of the construct naturally changes the construct's meaning. Objective indicators are more appropriate for use as causal indicators than are perceptual measures with error terms such as those commonly used to measure psychological constructs.

Finally, empirical conditions address statistical issues such as multicollinearity. Given the possibility for conceptual overlap among the proposed items, multicollinearity was viewed as a significant concern in terms of developing the technology enabled job learning construct as a formative measure.

Technology enabled job learning in this study was operationalized, using eight items that asked respondents how information technology influenced their job learning. Although there is a broad understanding that information technology is a learning tool and that it has the potential to help employees learn more about their jobs and how to perform better, to the best of our knowledge, there are no existing measures linking technology to job learning. However, we found a rich body of literature on productivity in organizations that was helpful in developing items for the technology enabled job learning construct. This literature provides a broad background for understanding how technology might influence individuals as they go about learning about their jobs and performing tasks (Braverman, 1974; Zuboff, 1988; Weick, 1990). This literature also suggests that information-rich organizations are learning environments with the purpose of being more productive (Zuboff, 1988). Job learning in this study was conceptualized in terms of how technology assists individuals to become more skilful at doing what they are supposed to do as well as helping them to better perform their assigned tasks.

On the basis of this literature review, survey items were generated to operationalize technology as it helps the individual learn 'how to do things, rather than what to do or why' (Zuboff, 1988, p. 206). This conceptualization also suggests that technology helps the individual to understand the job better as well as to perform it more effectively. The survey items also intended to assess whether information technology would increase employees' capabilities to enrich and expand jobs (Long, 1993). Examples of technology enabled job learning indicators in this study include: 'This application increases the ability required to do my job', 'This application helps me learn how to improve the quality of my work', 'This application increases the capabilities required to do my job', and 'This application helps me better understand my job'. We used a panel of several academics to obtain feedback and thus ensure content validity for these eight items prior to using them in the survey. The survey items were measured using a 5-point Likert-type scale anchored by: (1) 'Not at all' and (5) 'A great deal'. As discussed below, the technology enabled job learning measurement was found to be both reliable and valid.

In this study, the three-factor measurement model developed and validated by Torkzadeh & Doll (1998) was used to operationalize system use. The instrument consists of 13, 12, and 5 items for decision support, work integration, and customer service, respectively. Examples of system use items include: 'I use this application to control or shape the decision process', 'I use this application to plan my work', and 'I use this application to improve the quality of customer service'.

To measure technology outcomes, the four-factor measurement model of information technology outcomes developed and validated by Torkzadeh & Doll (1999) was used. Each of the four constructs (task productivity, task innovation, customer satisfaction, and management control) was measured using three items. Examples of technology outcomes items include: 'This application improves management control', 'This application helps me create new ideas', 'This application increases my productivity', and 'This application improves customer service'. System use and technology outcomes were measured using a 5-point Likert-type scale anchored by (1) 'Not at all' and (5) 'A great deal'.

Sample

A survey questionnaire comprising 30 items measuring system use, eight items measuring technology enabled job learning, and 12 items measuring technology outcomes was used to collect data (see Appendix A for the total list). The survey was also used to collect respondent information, type of application, and the level of use (reported below). We used our contacts in local and regional industries to collect data. Although a convenience sample, collecting data in this manner gave us the opportunity to survey practitioners who frequently used specific applications, and thus were familiar with what those applications were used for, and how those applications might have helped them in their job. Further, due to our close contacts, we were able to collect all the survey questionnaires.

The respondents relied on specific applications for completing their job functions; the instructions for respondents asked that the questionnaire be completed by individuals who were major users of an application and asked the respondents to identify a specific application as a reference when responding to the questions. By collecting data from users who relied on the use of a specific application, we were able to ensure that respondents could identify patterns of application use in their organizational context, how the application helped them learn about their job, and how they viewed the influence of job learning on their respective task outcomes. Demographics revealed a broad industry representation. Respondents worked for government agencies (19.5%), manufacturing (16.2%), health services (14.6%), transportation (12.6%), education (9.3%), finance (8.8%), wholesale and retail (4.9%), and others (14%). Several incomplete responses were discarded resulting in a final sample of 308 responses that were used for the subsequent analyses. Discarded responses were considered too few to suggest a meaningful difference between incomplete and complete responses. Major applications include office automation applications (22.5%), financial applications (20.9%), and accounting applications (13.5%). Respondents used specific applications 20 h per week for a minimum of 3 years, on average.

Data analysis and results

We used partial least squares (PLS-Graph 3.0) to analyze the proposed relationships. PLS is suitable because the aim of this study is to examine the predictive validity of the 'system use' measure on 'job learning' and the 'job learning' measure's influence on technology outcomes. Kolmogorov–Smirnov's test of normality indicates that our data were not normally distributed, providing an additional motivation for using PLS, given it is robust to violations of normality. All items were modeled as reflective according to their original design. The measurement and structural models were tested simultaneously. Since PLS does not produce fit statistics, we followed the general criteria of item loadings above 0.7, path coefficients above 0.2 (Chin, 1998b), and t-statistics for item loadings and path coefficients generated from bootstrapping (100 re-samples) to evaluate the analysis results.

Because the items for 'job learning' were developed for this study, we first ran an exploratory factor analysis to examine the factor structure for these items. All eight items loaded on one factor explaining 66% of the available variance, and demonstrated strong loadings ranging from 0.745 to 0.854. Cronbach's alpha for the eight items was 0.92 and all corrected item-total correlations were above 0.7, indicating acceptable internal consistency. Thus all eight items for the 'job learning' measure were retained.

Results of the PLS measurement model (item loading, cross-loading, t-statistics, composite reliability, and AVE) are presented in Appendix B. Most item loadings were above 0.7 and all loadings were significant, providing evidence of convergent validity (Gefen & Straub, 2005). Although a few items had marginal loadings, we decided to retain them to be consistent with the original instruments. Although some cross-loadings were observed, all items loaded highest on their respective factors except for one work integration item, which was subsequently eliminated. Given that work integration was measured reflectively, removing one item does not alter the definition of the construct. The composite reliabilities and AVE of all factors were above the accepted 0.7 and 0.5 level, respectively.

The discriminant validity of the measures was evaluated using the two-step process recommended by Gefen & Straub (2005). First, the cross loadings among the measurement items were examined. While no exact threshold was available, 'all the loadings of the measurement items should be an order of magnitude larger than any other loading' (Gefen & Straub, 2005, p. 93). Results depicted in the Appendix show that this first condition had been satisfied. Second, the square root of the AVE should be much larger than the correlations among any two constructs. Again, there is no exact threshold for how much larger the square root of the AVEs must be. For most of the constructs this condition also appears to have been satisfied. However, there are two cases in which the correlations were very close to their respective square-root of the AVE; work integration and decision support, and customer service and customer satisfaction. These results suggest that for these two cases, the second step recommended for establishing discriminant validity was only weakly supported. Given the satisfaction of the first condition recommended for establishing discriminant validity, the satisfactory composite reliability scores, and the marginal support for the second condition, we were reasonably confident that for these two cases, conceptually distinct constructs were being measured. Helping to explain the high correlation between work integration and decision support, it is plausible that certain decisions require significant levels of communication, and thus using systems for work integration would be highly relevant in the minds of those using systems to make decisions. The high correlation between customer service and customer satisfaction was somewhat expected, given the relationship between using a particular system for customer service and downstream perceptions of customer satisfaction. Results from the common method variance tests reported in Table 3 further indicate that the correlation between customer service and customer satisfaction was not due to method bias.

The results of the PLS structural model are presented in Figure 3. All three system use constructs significantly affected job learning with path coefficients ranging from 0.190 to 0.324, explaining over 40% ($R^2 = 0.433$) of the variance. Even though the path coefficient between work integration and job learning is just below the recommended criteria of 0.2, the t-statistic was significant. Effect sizes were calculated based on the procedure recommended by Chin (1998a, b), and were 0.4, 0.4, and 0.14 for the relationship between decision support, work integration, and customer service and job learning, respectively; indicating small to medium effects. These results support Hypotheses 1–3.

Supporting Hypotheses 4–7, technology enabled job learning was also significantly and positively related to the respective technology outcome constructs. Path coefficients ranged from 0.527 to 0.676, and job learning explained a significant amount of variance in the respective outcome constructs (0.277–0.457). Figure 3 graphically depicts the final results.

Common method variance

Common method variance is a concern in any study that employs a cross-sectional survey design. To address this concern in the current study, we conducted a series

Table 3 Measurement model results

Construct	*Decision support*	*Work integration*	*Customer service*	*Job learning*	*Management control*	*Task innovation*	*Task productivity*	*Customer satisfaction*
Decision support	**0.7937**							
Work integration	0.6920	**0.7273**						
Customer service	0.3809	0.4014	**0.8408**					
Job learning	0.5544	0.5274	0.5141	**0.8093**				
Management control	0.5714	0.5675	0.5007	0.6214	**0.8809**			
Task innovation	0.5488	0.5034	0.3592	0.6758	0.4292	**0.9088**		
Task productivity	0.4276	0.4021	0.4260	0.6743	0.5006	0.4476	**0.8746**	
Customer satisfaction	0.3595	0.3018	0.7769	0.5271	0.5337	0.3321	0.4458	**0.9359**

Bold = square root of AVE.

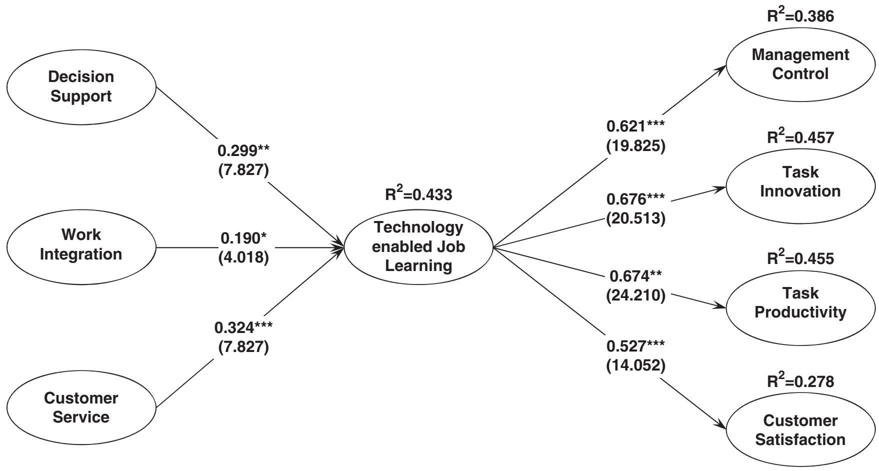

Figure 3 Structural model results.
Note: *$P<0.05$; **$P<0.01$; ***$P<0.001$; numbers in parentheses are *t*-statistics.

of additional tests. First, we employed the Harmon single factor test. This test evaluates whether common method variance is playing a significant role in the model by examining whether or not a large amount of variance is explained by a single factor. In the current study, an exploratory factor analysis revealed seven factors explaining 68.4% of the variance with no single factor accounting for more than 18.3%. Next, we conducted a latent common method variable test in which items are allowed to load on their respective constructs as well as on a common method factor (Podsakoff *et al.*, 2003). Results from this test revealed only small changes in R^2 when the common method factor was introduced into the research model (from 0.88 to 4.62%). In combination, these tests suggest that common method variance plays a minimal role in the current study (Wakefield *et al.*, 2008).

The final model depicted in Figure 3 shows how job learning could also be viewed as a mediating construct between system use and technology outcomes. In other words, this view of the model suggests that technology enabled job learning construct may represent a pivotal link between patterns of system use and the respective technology outcome categories. Although our results support the proposed hypothesized relationships between system use and job learning and between job learning and technology outcomes, examining job learning as a potential mediating variable can provide further evidence about the importance of job learning construct in the proposed research model. In the following section, we will describe our mediation analyses.

Post hoc mediation analyses

Statistical methods for assessing mediation have been discussed extensively in the literature. Some of the most well-known approaches were proposed by Kenny and his colleagues (Judd & Kenny, 1981; Baron & Kenny, 1986; Kenny *et al.*, 1998). These methods assess the direct effect of the independent variable (X) on the dependent variable (Y), both with and without the mediating variable (M) specified in the model. The degree of mediation is determined by assessing the change in the $X \rightarrow Y$ path across these conditions. Two important points about this approach are, (1) when the mediating variable is omitted the $X \rightarrow Y$ (c) path should be significant, and (2) when the mediating variable (M) is included in the model, a non-significant $X \rightarrow Y$ (c') path reflects total mediation.

Several new recommendations have been proposed for assessing mediation (MacKinnon *et al.*, 2002; Shrout & Bolger, 2002). These newer recommendations relax the requirement for a significant c path, and also propose methods for assessing partial mediation. The strength of the indirect effect is evaluated by multiplying the $X \rightarrow M$ (α) and $M \rightarrow Y$ (β) paths, and dividing the product by its standard error (MacKinnon *et al.*, 2002). The relaxation of the requirement for a significant c path as recommended by Baron & Kenny (1986) is to accommodate occurrences of suppression, or where distal relationships are being examined (Shrout & Bolger, 2002).

Neither of these conditions was present in the current study and therefore we applied both the classic approach championed by Kenny and his colleagues, and the newer methods recommended by MacKinnon *et al.* (2002), and Shrout & Bolger (2002). Combining these methods allowed us to provide the most comprehensive picture of the complex mediating processes potentially operating in the current model.

We began the assessment of the individual mediating relationships by first calculating α and β for each $X \rightarrow M \rightarrow Y$ in the structural model. To guard against Type II errors,

Table 4 Mediation analysis results

Relationship	α	β	z	p	(P_M)	*Mediation effect*
DS→JL→MC	0.562	0.450	3.793	0.0000	0.443	Partial mediation
DS→JL→TI	0.555	0.541	4.406	0.0000	0.545	Partial mediation
DS→JL→TP	0.551	0.632	5.323	0.0000	0.804	Total mediation
DS→JL→CS*	0.558	0.048	3.493	0.0005	0.723	Total mediation
WI→JL→MC	0.534	0.453	3.897	0.0000	0.423	Partial mediation
WI→JL→TI	0.523	0.574	4.595	0.0000	0.597	Partial mediation
WI→JL→TP	0.520	0.642	4.898	0.0000	0.878	Total mediation
WI→JL→CS*	0.531	0.509	3.938	0.0000	0.835	Total mediation
CS→JL→MC	0.516	0.499	4.255	0.0000	0.502	Partial mediation
CS→JL→T1	0.512	0.668	4.824	0.0000	0.656	Total mediation
CS→JL→TP	0.513	0.624	4.625	0.0000	0.748	Total mediation
CS→JL→CS*	0.517	0.170	2.390	0.0209	0.112	Partial mediation

Note: DS – decision support; WI – work integration; CS – customer service; JL – technology enabled job learning; MC – management control; TI – task innovation; TP – task productivity; CS* – customer satisfaction.

β was estimated with c' included in the model (Shrout & Bolger, 2002). The $\alpha\beta$ product was then divided by its standard error as calculated using Eq. 1 (Sobel, 1982). The result is a z score that can be used to determine the significance of the indirect effect.

$$\sigma_{aB} = \sqrt{a^2\sigma_B^2 + B^2\sigma_a^2} \qquad (1)$$

where σ denotes the standard error of aB, a denotes the path coefficient for the antecedent to the mediator, and B denotes the path coefficient from the mediator to the Dependent Variable.

Next, as recommended by Shrout & Bolger (2002), partial mediation was assessed using the effect proportion mediated ratio (P_M). This procedure involved dividing the $\alpha\beta$ product (calculated with c' included in the model), by c (Step 1 of Baron & Kenny (1986)). In cases where the c' path was non-significant, evidence of total mediation was noted. Table 4 depicts the results of the respective mediation analyses.

Discussion

Results of data analyses supported our contention that as people use information systems to facilitate their work in terms of decision support, work integration, and customer service, they learn more about the job they are performing. The enhanced learning about their job through information systems contributes to better outcomes from using the systems. The current study establishes the efficacy of technology enabled job learning as an important construct that links information system usage to outcomes.

The mediation analysis results in this study suggest that job learning mediates the relationship between patterns of system use and technology outcomes differently. For example, the results suggest 'partial mediation' for the role of job learning in the relationship between patterns of system use and management control. On the other hand, the results also suggest 'total mediation' for the role of job learning in the relationship between patterns of system use and task productivity. Finally, the results also suggest a mix of total and partial mediation for the role of job learning in the relationship between patterns of system use and task innovation as well as customer satisfaction. Although intuitively appealing and interesting, these findings have not been discussed or supported in any study. We offer our interpretation of these findings relative to mediating role of job learning.

Decision support tools, for example, are used for semi-structured or unstructured decision making. Thus, the level of learning due to the use of such tools may depend on the degree to which decisions or work processes are structured. Management control involves both structured and unstructured situational outcomes, and because of that it is difficult to expect job learning to have a mediating role in all cases. The results may also depend on the position of the decision maker in the organization (for example, senior executives are expected to be better informed about decisions processes). On the other hand, task productivity is often well-defined; individuals are aware of what they are expected to accomplish and they learn how to achieve that using the system. Therefore, 'total mediation' through learning takes place. The interpretation of mediation analysis results relative to management control and task productivity draws on the purpose and nature of technology outcomes.

Task innovation is partially mediated by job learning when individuals use systems for decision support or work integration. Systems that are used for decision support or work integration in some cases may offer innovative ways to accomplish work and thus there is no need for the individual to learn to innovate. On the other hand, task innovation is totally mediated by job learning when individuals use systems for customer service. Using information systems, employees learn about customers and their needs and then seek to innovate ways to better serve those needs. Even if the fit between a system and a particular task is low, using the system might prompt the individual to learn, and the learning could still improve performance. This suggests that this study's findings offer a more general way of thinking about the outcomes of system use rather than requiring an assumption of fit as in some research studies (Goodhue & Thompson, 1995). Similar interpretation is feasible for how job learning may mediate the relationship between patterns of system use and customer satisfaction. Our interpretation of the mediation results relative to task innovation and customer satisfaction draws on the purpose and nature of system use.

Below, we describe the implications of our findings for research and practice, and outline potential future research work.

Research implications

The theoretical implications of this study's findings are associated with the pivotal role of technology enabled job learning in the relationship between patterns of system use and technology outcomes. People interact with information systems to accomplish organizationally relevant tasks. Formal education provides individuals with the necessary skills to start a job and to be able to manage routine and previously defined tasks. However, a great deal of what goes on in day-to-day operations is not routine or previously defined. On-the-job learning has become an integral part of work in most environments. Information technology helps individuals to search and locate job-related material online, make work inquiries to their colleagues, and experiment with alternative solutions. As a result, they learn more about their jobs.

The measurement of information technology use in information systems research has progressed from the traditional focus on the level and frequency of computer use to a conception that incorporates intent and patterns of use. Research interest in this domain has moved from how much technology is used to ways in which technology is used. This latter conceptualization has implications for evaluating technology outcomes on work; how we evaluate the influence of system use on the nature of work and productivity.

The move in research from design and acceptance of technology toward downstream research on consequences of the outcomes of technology on work at the individual and organizational level is evident. It is difficult to imagine how information technology application can be assessed without examining the influence it may have on the development and expansion of task-related know-how. Technology enabled job learning is both a direct consequence of system use and a major factor determining individual and organizational outcomes.

Technology enabled job learning is both a new form of labor and an increasingly acceptable measure of return on investment. Employees see and value the role of information technology in their skill development and in turn in their empowerment within organizations. The traditional approach to job learning through workshops and seminars has in many instances been replaced with on-going on-the-job experimentation and self-learning. Information technology enables 'learning organizations' to create work environments where 'learning to learn' occurs and collective know-how for task management is enhanced.

Individuals interact with technology applications to explore ways to improve their job performance, and in that fusion of exploring and doing, they learn and enhance their knowledge about their jobs. Learning becomes a part of what they need to do in order to perform better. Learning processes occur in the context of work; employees learn as they go about solving problems (Bereiter, 2002). In evaluating technology outcomes, we must go beyond what individuals currently do and examine how prepared they are to perform their jobs in the future. Formal training is expected to provide the individual with core competency and fundamental knowledge needed to learn on the job. Information technology is a pivotal tool that enables the individual to gain the necessary and timely knowledge for better management of tasks at hand.

The potential mediating role of technology enabled job learning may also aid us in gaining a better understanding of why some system use does not lead to desired organizational outcomes, or why the outcomes associated with the use of a similar technology application vary across organizations. It may be as important to understand and measure the level of job learning due to technology use, as it is to understand the antecedents of technology acceptance. Issues of antecedents and individual preferences for technology acceptance have received a great deal of attention in information system research in recent years and that increased attention is appropriate.

Employee skills are developed in a learning environment that includes work settings, tools, problems, and co-workers who have a common purpose (Lambrecht *et al*., 2004). Because we are evaluating the influence of technology in organizational contexts we are also evaluating the interaction of people and technology in an organizational environment rather than separately evaluating the individual, the technology, or the organization. This conceptualization is helpful in explaining the perception of a widening gap between the potential of information technology and its actual use; it represents a major contribution toward work in this important area.

Practical implications

This view of system use and technology outcomes in an organizational context influenced the researchers during the design and implementation of the current study. Our premise is that when information technology is used by individuals in new ways, interactive effect has important implications for the nature of work, the need to learn and innovate, and the approach to decision problems. Specifically in this respect, our objectives were: (a) to evaluate system use in terms of a 'function' that individuals could easily relate to in their work context (to rationalize decisions, to make sense out of data); (b) to evaluate organizationally relevant technology outcomes (improved customer service, improved productivity); (c) to evaluate technology enabled job learning as a behavior that links system use with the perceived outcomes of technology; and (d) to extend the conception of technology outcomes beyond the traditional focus on productivity and management control and to include dimensions of customer satisfaction and task innovation that are relevant to the success and survival of modern organizations.

These objectives make the findings of our study relevant and useful to the management of technology. Although system use was traditionally measured in terms of frequency and the level of use, the conceptualization of system use in terms of patterns of use, where an application is evaluated in the context of organizationally relevant tasks, is more meaningful to practice. Similarly, measures of technology outcomes that influence the structures and functions of work to improve employee productivity are intuitively appealing to those who manage technology. These measures extend the traditional view of technology outcomes that emphasize productivity and management control to include measures of task innovation and customer satisfaction that are important in an organizational context.

The measures of technology enabled job learning developed for this study are reliable and easy to use in practice. If technology return on investment is to be assessed, for example, in terms of its influence on the accumulation of task-related know-how for the individual, it is important that those measures capture functionally relevant new learning. These measures provide several advantages to information system executives: (a) they can help management identify effective applications; (b) they can help management evaluate individual and organizational learning; and (c) they can help management in their technology portfolio development.

Study limitations

As is the case with most empirical studies, this study too has its limitations. We caution the reader to take into account these limitations when interpreting our findings. First, all measures in this study are perceptual and to that extent respondents expressed their beliefs regarding survey questions. Second, data for this study were collected using a cross-sectional survey design suggesting that common method bias and self-report bias are potential areas of concern. We carried out two common method variance tests and found that common method variance did not significantly influence study findings. Nonetheless, these results should be interpreted with these limitations in mind. Further, although the hypotheses presented in this study are supported by the literature, the manner of data collection does not support the evaluation of causality. Therefore, only tentative conclusions about the relationships in the proposed model may be drawn.

Future work

Several areas merit further research attention. First, we encourage confirmatory studies of the new measures of technology enabled job learning; new data are required to confirm the reliability and validity of the recommended measures. Second, we encourage confirmatory studies for specific industries (e.g., service industry, entertainment industry, etc.), in specific settings (e.g., in an environment where user participation in system development is strong or where the majority of developmental activities are offshored), and for specific technologies (e.g., CRM). Studies that are more focused on an industry, environment, or technology would demonstrate the potential benefits for research and practice in these specific settings. For example, part or all of the system use and technology outcomes constructs may be appropriate in these environments, leading to additional insights into the application of these measures. Third, a longitudinal study that examines the mediating role and influence of technology enabled job learning between system use and outcomes for specific applications will provide valuable insights into the development and management of 'learning organisations'. Fourth, work environment (which includes, e.g., co-workers, management style, and common purpose) is expected to influence individual learning. Given this expected influence, it may be useful to explore the extent and nature of technology enabled job learning in different settings. These study findings can help us understand, for example, what facilitates a high-quality organizational learning environment.

Conclusion

In this study, we used survey data to (a) examine the link between patterns of systems use proposed by prior information systems research (i.e., system use to support decisions, to integrate work, and to serve customers), and job learning; (b) examine the link between job learning and categories of technology outcomes proposed by information systems research (i.e., technology outcomes on management control, task innovation, task productivity, and customer satisfaction); and (c) explore the possibility of technology enabled job learning as a mediating variable in the relationship between patterns of system use and the technology outcome categories.

To examine the relationships described above, we used two previously published instruments for 'systems use' and 'information technology impact'. We developed new measures of 'technology enabled job learning' for this study. These new measures are reliable, valid, and easy to use for future research. System use, as we have argued in this paper, does not directly lead to outcomes. Technology enabled job learning helps to provide a link between system use and technology outcomes.

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Appendix A

See Table A1.

Table A1 Item description

Decision support	
DS1	I use this application to rationalize my decisions.
DS2	I use this application to make the decision process more rational.
DS3	I use this application to help me make explicit the reasons for my decisions.
DS4	I use this application to control or shape the decision process.
DS5	I use this application to decide how to best approach a problem.
DS6	I use this application to improve the effectiveness and efficiency of the decision process
DS7	I use this application to help me justify my decisions.
DS8	I use this application to check my thinking against the data.
DS9	I use this application to make sure the data matches my analysis of problems.
DS10	I use this application to help me think through problems.
DS11	I use this application to analyze why problems occur.
DS12	I use this application to make sense out of data.
DS13	I use this application to help me explain my decisions.
Work integration	
WI1	I use this application to coordinate activities with others in my work group.
WI2	I use this application to exchange information with people in my work group.
WI3	I use this application to communicate with other people in my work group.
WI4	I use this application to communicate with people I report to.
WI5	My work group and I use this application to coordinate our activities.
WI6	I use this application to keep my supervisor informed.
WI7	I use this application to plan my work.
WI8	I use this application to exchange information with people who report to me.
WI9	I use this application to help me manage my work.
WI10	I use this application to get feedback on job performance.
WI11	I use this application to communicate with people who report to me.
Customer service	
CS1	I use this application to improve the quality of customer service.
CS2	I use this application to serve internal and/or external customers.
CS3	I use this application to more creatively serve customers.
CS4	I use this application to deal more strategically with internal/external customers.
CS5	I use this application to exchange information with internal/external customers.

Table A1 Continued

Job learning	
JL1	This application increases the skill required to do my job.
JL2	This application increases the capabilities required to do my job.
JL3	This application makes me more skillful in my work.
JL4	This application helps me learn how to be more productive on my job.
JL5	This application helps me learn how to improve the quality of my work.
JL6	This application helps me learn how to do my job.
JL7	This application helps me better understand my job.
JL8	This application increases the ability required to do my job.
Management control	
MC1	This application helps management control performance.
MC2	This application helps management control the work process.
MC3	This application improves management control.
Task innovation	
TI1	This application helps me create new ideas.
TI2	This application helps me come up with new ideas.
TI3	This application helps me try out innovative ideas.
Task productivity	
TP1	This application allows me to accomplish more work than would otherwise be possible.
TP2	This application increases my productivity.
TP3	This application saves me time.
Customer satisfaction	
CS1	This application improves customer service.
CS2	This application improves customer satisfaction.
CS3	This application helps me meet customer needs.

Appendix B

See Table B1.

Table B1 Factor loadings, cross loadings, reliabilities and t-statistics

Variables	*Decision support*	*Work integration*	*Customer service*	*Job learning*	*Management control*	*Task innovation*	*Task productivity*	*Customer satisfaction*	*t-value*
Decision support (Composite reliability = 0.957, AVE = 0.630)									
DS1	**0.872**	0.619	0.258	0.452	0.465	0.528	0.334	0.251	75.458
DS2	**0.854**	0.594	0.347	0.460	0.490	0.478	0.372	0.333	52.206
DS3	**0.822**	0.552	0.256	0.430	0.494	0.482	0.376	0.259	48.695
DS4	**0.815**	0.551	0.365	0.421	0.509	0.366	0.309	0.360	43.948
DS5	**0.812**	0.566	0.369	0.456	0.447	0.475	0.270	0.358	47.310
DS6	**0.804**	0.595	0.350	0.466	0.458	0.421	0.407	0.324	40.934
DS7	**0.802**	0.559	0.294	0.356	0.421	0.398	0.260	0.254	37.819
DS8	**0.785**	0.543	0.227	0.418	0.413	0.457	0.284	0.207	42.120
DS9	**0.784**	0.538	0.286	0.490	0.490	0.364	0.341	0.308	45.782
DS10	**0.779**	0.496	0.287	0.408	0.416	0.433	0.354	0.236	36.395
DS11	**0.773**	0.570	0.268	0.478	0.451	0.472	0.327	0.260	34.743
DS12	**0.703**	0.439	0.353	0.508	0.433	0.427	0.425	0.318	27.321
DS13	**0.691**	0.512	0.232	0.276	0.369	0.307	0.309	0.180	26.221
Work integration (Composite reliability = 0.925, AVE = 0.529)									
WI1	0.546	**0.832**	0.355	0.418	0.460	0.414	0.302	0.248	42.751
WI2	0.460	**0.785**	0.315	0.344	0.349	0.404	0.286	0.177	36.492
WI3	0.472	**0.779**	0.273	0.362	0.297	0.397	0.313	0.155	37.216
WI4	0.502	**0.751**	0.275	0.387	0.392	0.363	0.344	0.158	33.874
WI5	0.446	**0.711**	0.324	0.364	0.458	0.288	0.257	0.296	22.705
WI6	0.483	**0.711**	0.168	0.341	0.420	0.273	0.281	0.128	27.342
WI7	0.512	**0.695**	0.292	0.381	0.413	0.388	0.250	0.289	24.008
WI8	0.492	**0.686**	0.299	0.235	0.290	0.303	0.200	0.151	24.287
WI9	0.508	**0.678**	0.273	0.471	0.527	0.381	0.363	0.221	28.339
WI10	0.571	**0.678**	0.359	0.493	0.492	0.424	0.301	0.354	25.896
WI11	0.496	**0.677**	0.222	0.249	0.279	0.314	0.241	0.118	23.226
Customer service (Composite reliability = 0.923, AVE = 0.707)									
CS1	0.322	0.308	**0.884**	0.440	0.456	0.307	0.359	0.776	57.978
CS2	0.299	0.289	**0.880**	0.409	0.388	0.232	0.375	0.679	50.651
CS3	0.328	0.321	**0.871**	0.499	0.462	0.373	0.358	0.746	57.923
CS4	0.377	0.366	**0.817**	0.420	0.406	0.274	0.343	0.560	38.546
CS5	0.272	0.417	**0.746**	0.379	0.383	0.311	0.360	0.471	23.375

Table B1 Continued

Variables	*Decision support*	*Work integration*	*Customer service*	*Job learning*	*Management control*	*Task innovation*	*Task productivity*	*Customer satisfaction*	*t-value*
Job learning (Composite reliability = 0.938, AVE = 0.655)									
JL1	0.406	0.352	0.433	**0.845**	0.448	0.555	0.526	0.434	54.016
JL2	0.376	0.364	0.450	**0.840**	0.451	0.501	0.609	0.470	53.106
JL3	0.453	0.394	0.394	**0.827**	0.469	0.546	0.610	0.444	51.259
JL4	0.414	0.434	0.392	**0.824**	0.516	0.608	0.565	0.378	43.292
JL5	0.405	0.432	0.341	**0.812**	0.490	0.632	0.550	0.351	43.613
JL6	0.539	0.527	0.415	**0.797**	0.550	0.577	0.430	0.391	37.778
JL7	0.584	0.522	0.483	**0.783**	0.655	0.527	0.505	0.501	37.345
JL8	0.370	0.356	0.405	**0.738**	0.401	0.413	0.581	0.431	26.718
Management control (Composite reliability = 0.912, AVE = 0.776)									
MC1	0.550	0.516	0.450	0.594	**0.897**	0.410	0.480	0.516	93.700
MC2	0.474	0.524	0.479	0.554	**0.883**	0.402	0.460	0.458	52.706
MC3	0.482	0.455	0.389	0.485	**0.863**	0.314	0.372	0.430	45.971
Task innovation (Composite reliability = 0.934, AVE = 0.826)									
TI1	0.489	0.466	0.304	0.592	0.372	**0.926**	0.420	0.278	103.155
TI2	0.512	0.474	0.352	0.602	0.440	**0.910**	0.385	0.291	95.778
TI3	0.495	0.434	0.323	0.646	0.360	**0.891**	0.415	0.333	70.492
Task productivity (Composite reliability = 0.907, AVE = 0.765)									
TP1	0.386	0.376	0.378	0.633	0.472	0.385	**0.898**	0.388	63.401
TP2	0.400	0.353	0.373	0.632	0.424	0.439	**0.880**	0.406	67.170
TP3	0.329	0.321	0.368	0.483	0.415	0.341	**0.846**	0.375	40.167
Customer satisfaction (Composite reliability = 0.954, AVE = 0.876)									
CS1	0.337	0.293	0.755	0.461	0.520	0.290	0.405	**0.942**	111.503
CS2	0.300	0.274	0.710	0.495	0.476	0.303	0.404	**0.933**	97.125
CS3	0.370	0.280	0.715	0.518	0.501	0.336	0.438	**0.928**	88.866

Note: Boldface numbers are loadings of indicators to their own construct.