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Learning in Enterprise System Support: Specialization, Task Type and Network Characteristics

Research-in-Progress

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Abstract

In this paper, we introduce two contingency factors --task type and network characteristics—that examine how individuals learn from experience. We hypothesize that task specialization and variation have positive impacts on IS professionals' learning from experience. We further hypothesize that this performance effect of learning is contingent upon task type and characteristics of domain-specific knowledge networks. In particular, specialized experience will be more beneficial to learning when a task is a locating task-type or when network centrality is high. In contrast, varied experience will be more beneficial when a task is a diagnosing task-type or when network betweenness is high. The research model will be validated in the context of post-implementation enterprise system support. The study incorporates a social network perspective to study learning by experience, and contributes to the knowledge management field. Findings will provide practical insights on managing IT human capital and improving IS support services.

Keywords: IS professional, learning, knowledge management, ERP support, social network analysis

Introduction

Organizations often rely on information system (IS) professionals to train employees on using new systems, resolving system use problems, and modifying software applications to meet new business requirements. It is commonly acknowledged by both IS academia and industry practitioners that system support and maintenance account for the largest efforts in information system (IS) development. To support and maintain information systems, an IS professional interacts with organizational end-users and engages in extensive knowledge work that involves providing information, knowledge, diagnoses and solutions to end-users (customers) in a timely manner (Das 2003; Santhanam et al. 2007). Because of these, improving productivity of the knowledge workers becomes crucial to achieving effective system use and resource utilization for many organizations.

Whether to educate their customers about system features or to diagnose system errors, IS professionals rely on their ability to apply existing knowledge about technical systems and about customers' business domains. Moreover, in the context of information system support where technologies are integrated and a customer's business environment evolves, IS professionals increasingly face the challenge of keeping up with the latest technological advancements and new business requirements. Hence, learning, the process of acquiring knowledge and developing skills, has become critical to those professionals' productivity. As Ellis (1965) explains, individuals' learning not only demonstrates the transfer of content knowledge (gained from working in previous unit) to a new unit of tasks, but also reflects their enhanced learning ability, or the ability to assimilate or process acquired information and knowledge to a new and different problem domain.

Knowledge management and learning scholars traditionally focus on two factors in learning: specialization and variation. Specialization refers to the degree to which an individual or group performs a narrow range of activities, while variation focuses on dispersing efforts across a variety of activities (Schilling et al. 2003). Extant studies have examined the role of specialization and variation in lab experiments of playing strategic games (Schilling et al. 2003) or in the field study of software maintenance (Boh et al. 2007; Narayanan et al. 2009). These studies suggest that variation and specialization must be balanced to maximize learning (Narayanan et al. 2009), and that their benefits can be maximized at different levels of analysis (Boh et al. 2007). Although prior studies provide useful insights, it still remains unclear under which conditions one should emphasize specialization or variation.

In this paper, we introduce two contingency factors --- task type and network characteristics --- to the learning benefits of specialization and variation. Our research adopts the perspective of knowledge management and social network analysis, and focuses on IS professionals' learning processes with regard to two different types of tasks, within a knowledge network of peers. Specifically, we argue that the learning processes will differ as a result of customer problems that are brought to the attention of an IS professional, as well as interactions among IS professionals. These arguments will allow us to answer the research question: *When should specialization or variation be emphasized in learning?*

To investigate the contingency effect of specialized experience and varied experience, our study focuses on the context of enterprise system support. This context is appropriate for our research because support of enterprise-wide systems often relies not only on IS professionals' familiarity with a particular software module (e.g., HR/Payroll system), but also on their knowledge of the integration across multiple software modules (e.g., between HR/Payroll system and Finance system). This research-in-process study has potential to make several contributions to theory and practice. By focusing on contingency factors at the individual level, this study contributes to the management and learning research by investigating the conditions under which a knowledge worker should specialize or diversify their experience. Additionally, focusing on post-implementation enterprise system support, this study enhances our understanding of IS professionals in system support environment, and suggests ways for IS managers to improve IS support efficiency.

The paper is organized as follows. We first discuss the theoretical foundations that guide our research framework and hypotheses development. We then describe the research method (including research site and data sources) and present the contingency model of learning. We also describe our plan to analyze data and conclude with potential implications for research and practice.

Theory and Hypotheses

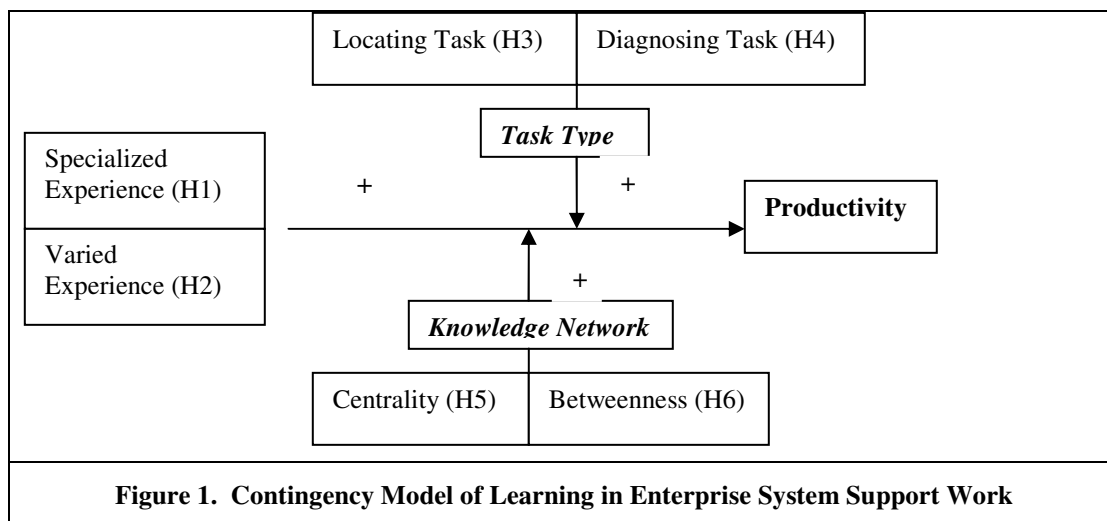
Knowledge Work in Information System Support

Enterprise system support provides IS professionals with a dynamic context to apply and utilize different types of knowledge in their support work. Enterprise systems, such as SAP/R3, embed generic and commonly adopted business processes, often named “best practices”. Assimilation of these business practices has become one of the biggest challenges to organizational end-users (Robey et al. 2002). To help users overcome these challenges, an IS professional must acquire knowledge about those processes and their integration into the tasks of the organizational end-users. In other words, they need conceptual knowledge of the system functions to support business tasks (“know-what”), and procedural knowledge of the sequence of operations to complete a business task (“know-how”) (Santhanam et al. 2007). Additionally, enterprise systems offer the benefit of integrating processes across business functions (Davenport 1998). This integrated structure requires business functions to adopt a common view of data and work flows. Thus, knowledge about the data and work flows, the “know-why” (Santhanam et al. 2007), would enable IS professionals to better assist frustrated end-users who are coping with system-imposed business change.

The complexity of an enterprise system is due not only to its integrative structure and enterprise scope, but also to its variety of configurations (e.g., more than 8,000 configuration tables in the commercial software of SAP/R3). As a result, organizations often encounter significant barriers when learning ERP configurations (Robey et al. 2002). In this case, technical knowledge about enterprise systems’ configuration becomes useful when a system-use problem requires manual fixing in the configuration tables. Hence, IS professionals’ knowledge about the configuration details is likely to help speed up their problem resolution.

One way to evaluate performance of the knowledge workers in this respect is to examine their productivity, or the time/effort they spend on resolving customer problems (Das 2003). With this conceptualization of productivity, we focus on learning as an aspect of productivity that occurs when IS professionals repeatedly and consistently resolve problems, interact with customers, and communicate with other IS professionals. In other words, we investigate the influence of the nature of the knowledge (e.g., type of tasks) and the influence of the peer knowledge network (e.g., network characteristics) on an IS professional’s learning outcome and productivity.

Our proposed research model includes hypotheses with regard to three sets of variables and their impacts on productivity and learning: 1) specialization vs. variation, 2) task types (locating vs. diagnosing), and 3) knowledge network characteristics (centrality vs. betweenness). In summary, we hypothesize that task specialization and variation have positive impacts on individual learning. In addition, task specialization will be more beneficial to learning outcome when a task is a locating type, or when peer knowledge network centrality is high. In contrast, task variation will be more beneficial to learning when a task is a diagnosing type, or when peer knowledge network betweenness is high. Our main hypotheses are included in the contingency model of learning reflected in Figure 1.



Specialization vs. Variation

Although specialization and variation can apply to organization, group or individual levels, we focus on the individual level for two reasons. First, organization or group learning is a function of individual learning (Simon 1991); thus, clarification of factors contributing to individual learning can provide insights applicable to organization and group level learning as well. Second, system use problems are often assigned to individuals instead of groups, therefore, performance of an IS support professional directly affects the overall quality of IS support service.

An individual's specialization, or the degree to which an individual or group performs a narrow range of activities (Schilling et al. 2003), is believed to maximize the learning rate on a task (Dutton and Thomas 1984). In other words, as individuals accumulate experience while performing certain tasks, their productivity improves as they complete incoming tasks faster and better. This learning benefit of specialization has also been evidenced in software development and maintenance. For example, more experience in software development leads to shorter development time (Banker and Slaughter 1997). Moreover, the more experience a developer has with regard to a system, the better he will perform in modifying the focal system because the developer benefits from mastering the application codes and system architecture of the focal system (Boh et al. 2007). In enterprise system support, an IS professional's prior experience with resolving the same problems repeatedly allows the individual to quickly locate the required information and solve problems in the same domain more efficiently. Thus, based on these arguments, we predict,

HYPOTHESIS 1 (H1). Specialized experience of an IS professional is positively associated with productivity in system support work.

On the other hand, variation can be critical for developing new capabilities, especially the absorptive capability that enables a firm to evaluate and utilize knowledge from external sources. In other words, learning skills can be transferred across different problem domains even if the domain content is substantially different (Ellis 1965). It has been shown that analogous solutions to new problem domains are possible because of this (Mayer 1996). Furthermore, variation prevents possible "learning myopia" and "competency traps" (Levinthal and March 1993). Schilling et al. (2003) decomposes variation into two categories (related vs. unrelated variation), and uses an experimental design to investigate group performance under three conditions: specialization (playing only the strategic board game *Go*), related variation (mixing playing *Go* with playing a similar strategic board game *Reversi*), and unrelated variation (playing *Go* with an unrelated card game *Cribbage*). Their study suggests that group learning is significantly greater under the condition of related variation, because experience in related problem domains enables the groups to develop a deeper cognitive structure that applies to both domains.

In the context of enterprise system support, efforts of IS professionals are complicated by the system's integrative structure and enterprise scope. One of the main characteristics of an enterprise system is "the extensive integration it provides among the subunits of a business" (Gattiker and Goodhue 2005; p.560). When supporting such an integrated system, an individual's exposure to various business domains (sub-modules) is likely to increase one's knowledge of the integrated business processes and data, which facilitates problem solving. For example, configuration decisions for "Accounts Payable" under the "Payment" module reflect the consolidation of data and integration of work flows across accounting, finance and a business unit, facilitating a three-way matching among purchase orders, invoices and receipts for payment disbursement. Having experience in each of the domains would enable a support professional to address purchase-order process problems more efficiently, because he understands the process-oriented view of the system. Another implication of being assigned to support a variety of software sub-modules is that an individual has exposure to various kinds of problems and is able to access to a bigger pool of knowledge experts, both of which can facilitate an individual's problem solving. Thus, we argue,

HYPOTHESIS 2 (H2). Varied experience of an IS professional is positively associated with productivity in system support work.

In addition to the effects of specialization and variation on individual learning, scholars from management and information systems have also examined the learning outcomes of task specialization and variation. First, Schilling et al.'s study (2003) of 3-member student groups suggests that group learning rates are significantly greater under the condition of related variation, rather than under the condition of either specialization or unrelated variation. Consequently, Boh et al. (2007)'s study of software maintenance provides evidences to support that task variation and specialization influence learning and productivity at different levels of analysis: groups or organizational units' productivity improves with accumulated experience with related systems (related variation) as members in the

groups pool and share their specialized knowledge expertise, while individual's learning rate benefits the most from specialization. Similarly, a recent study on offshore software service demonstrates that both variation and specialization can help improve an individual developer's performance, but too much of either can become detrimental (Narahanan et al. 2009).

The studies mentioned above imply a contingency effect of specialization and variation on learning. Using the knowledge-intensive system support as the research context, our study turns to examine the two factors in more detail below: types of support task, and knowledge network of IS support professionals.

Type of Support Task: Locating and Diagnosing

Learning is maximized through specialization because individuals can focus time and energy on one particular kind of task and gain an in-depth understanding of a specific problem domain. The new task must be similar to the previous task to allow knowledge transfer from the previous experience (Ellis 1965). One common task in supporting an information system is to locate and provide customers with information regarding the "what/when/where/how" of system use, including questions such as "Where can I locate the vendor names for my purchase order?" or "How do I create a purchase order online?" Because completion of these tasks requires locating appropriate information and transferring the knowledge to customers, we categorize this type of task as a "locating" task, which is similar to the task of "informational retrieval" and "plan synthesis" in Das' study (2003).

Usually, a locating task, such as searching for information on a system feature or procedure, is similar to tasks performed in the past, thus making it a good candidate for experience specialization. When a support professional remembers the source of the information, he can locate it and respond to new requests quickly. As long as similarity is found between two locating tasks, the support professional can utilize the existing resources and solutions to respond to new tasks (Das 2003). Therefore, a locating task would benefit more from specialization (than from variation) because the professionals may have developed an in-depth understanding of the task and problem from their dedication to the same problems over time. Thus, we hypothesize,

HYPOTHESIS 3 (H3). Specialized experience of an IS professional will be strongly associated with his productivity when the task type is locating.

Meanwhile, there are cases when a new problem cannot be matched with previously reported problems. For example, when a system fails due to erroneous operations caused by the technical system or by the interaction between the system and a user, IS professionals diagnose the cause of the problem and develop resolution strategies. Examples include "Why does my online purchase order display an incorrect amount?" or "Why does an error message appear when I try to add a new employee's information?" We refer this type of task as a "diagnosing" task, which resembles tasks of "state abstraction" or "abductive diagnosis" in Das' study (2003).

Completion of a "diagnosing" task requires new solutions to be generated, based on reasoning drawn from an individual's previous background and principles of various disciplines (Das 2003). Such tasks are costly, but unavoidable in software support due to the high novelty of this field. Performing this kind of task will benefit from a wide range of knowledge bases because individuals may draw on synergies across different disciplines to identify resolution strategies. Varied experience may expose individuals to various sources of information and knowledge. Moreover, the deeper cognitive structure and "schema" developed from various problem domains can facilitate individuals transferring their learning across different yet related problem domains (Schilling et al. 2003). Hence, we predict,

HYPOTHESIS 4 (H4). Varied experience of an individual will be strongly associated with the individual's productivity when the task type is diagnosing.

Knowledge Network Characteristics: Centrality and Betweenness

An enterprise system includes multiple application modules to serve different business functions, ranging from payroll administration to supply chain management. When supporting an enterprise system, an IS professional is often assigned to a module-specific team, such as a "Human Resources (HR) / Payroll" team, which addresses all the requests and problems with regard to the HR/Payroll module in an enterprise system. However, within the module-specific team, one can be assigned to focus on a dedicated domain, such as "Payroll", or can be assigned to support multiple domains including "Benefits" or "Personal Administration", all of which belong to the HR/Payroll

module. By working within and across domains, IS professionals may come to draw on or rely on the knowledge of other IS professionals for task completion. This learning occurs differently though, depending on the problems reported to an individual. For example, increased learning opportunities in a specific domain (e.g., payroll) are likely to speed up the learning rate with regard to that specific domain. However, increased learning opportunities across different domains may decrease learning rates within the focal domain but may improve an IS professional's productivity in performing diagnostic tasks. Along the same lines, IS professionals may come to share knowledge and information with respect to one particular business domain. Or, they may come to share knowledge and information with respect to diverse business domains.

Given the knowledge intensity of information system support work, our study incorporates social network measures in our learning model. We focus on an individual's collection of knowledge from different business domains, as well as individual level connections with peers, or other knowledge workers, across different business domains. Peer networks and alliances have been found to act generally as sources of information (Gulati 1995) or to broker opportunities for learning (Obstfeld 2005). Recently, Sykes and colleagues (2009) studied post-implementation system use and found that employees' chances of accessing resources in a peer network helped them gain knowledge needed for effective use of system features. In line with previous research (Leonard and Sensiper 1998), we refer to this collection of knowledge as a knowledge network, and conceptualize how peer-to-peer networks help workers gain knowledge. Specifically, we employ two network-related concepts to better conceptualize effects of this knowledge network. These two concepts are degree centrality and betweenness centrality.

Degree centrality in its traditional conceptualization refers to the sum of direct ties that involve a focal individual (Wasserman and Faust 1994). An actor with the most number of ties become the most central and active actor in the network. In our study, degree centrality refers to an IS professional's involvement in a domain-specific knowledge network of his peers; that is, degree centrality integrates the number of tasks and the number of IS professionals associated with the same domains as the focal IS professional. When an individual is high in degree centrality, the individual may be an "expert" in a particular domain and tasks, knowledge, or information associated with the domain. Therefore, an IS professional that is high in degree centrality would be more productive in task specialization (rather than task variation) because the IS professional may have developed an in-depth understanding of the task from their dedication to similar issues over time. As a result, this individual may improve productivity quickly based on the specialization of experience. For this reason, we predict,

HYPOTHESIS 5 (H5). Specialized experience of an IS professional will be strongly associated with his productivity when knowledge network degree centrality is high.

Varied experience may expose individuals to various sources of information and knowledge, thus improving their ability to assimilate or process acquired information and knowledge in new and different problem domains (Ellis 1965). Moreover, the deeper cognitive structure and "schema" developed from various problem domains can facilitate individuals transferring their learning across different yet related problem domains (Schilling et al. 2003). We expect to use betweenness centrality to conceptualize an individual's access to knowledge pools of diverse domains.

Betweenness centrality (shortened for "betweenness") in its traditional conceptualization refers to the ratio of flows that include individuals on the module-specific team versus the flows that do not include individuals on the module-specific team (Wasserman and Faust 1994). In teams that evidence high betweenness in the knowledge network, an individual is likely to have access to diverse knowledge and experience accumulated by his colleagues, enhancing his learning ability and performance. This will be more beneficial to those individuals with varied task experience, as they draw on synergies across different knowledge bases and cognitive schema. This in turn could lead to higher variation in productivity for those particular IS professionals. Hence, we predict,

HYPOTHESIS 6 (H6). Varied experience of an IS professional will be strongly associated with his productivity when the knowledge network betweenness is high.

Research Method

Research Site and Data Sources

The research site, hereafter referred to as “GiantOrg” (a pseudonym), is a large private enterprise located in the northeastern region of the United States. With a total of 40,000 personnel on its payroll, GiantOrg has under its umbrella four different institutions (two hospitals and two educational institutions), which operate independently, not only in their primary functions (e.g., patient care vs. education and research), but also in their administrative functions such as human resources, accounting, finance and supply management. Their business processes were primarily mainframe system –based, shadow system-based and paper based. As a result of their non-integrated business processes, more than 1000 disparate information systems had been developed or purchased by GiantOrg during the last three decades. In an effort to integrate and streamline many of its business functions, GiantOrg made a decision in mid 2003 to implement an enterprise-wide system across its four institutions. After evaluating three enterprise system vendors, it selected an ERP package SAP/R3, and chose to implement four modules of the SAP package, including human resource/payroll management, finance management, supply chain, and special project management. With a \$200 million budget, the four-site SAP implementation project started in December 2003 and completed in January 2007. When the SAP system went live in January 2007, GiantOrg’s Support Center became responsible for providing a centralized system support to 11,000 users throughout its four sites.

This study is part of a five-year (2004-2009) longitudinal field study on organizational implementation of an enterprise system. The study reported here focuses on its post-implementation phase (January 2007 –March 2008) and examines the learning behavior of IS professionals at the Support Center. The primary source of data is an archive of 24, 000 ticket records extracted from GiantOrg’s ticket-tracking database for the period of April 2007 -- March 2008. It contains data on the sequence of activities in solving an enterprise system problem, from the problems’ origin, to its categorization and assignment, and to the final resolution of the problem. GiantOrg started to use the ticket tracking system on April 1, 2007, three months after the go-live date. For the first three months when electronic records are not available, we have collected paper records of tickets.

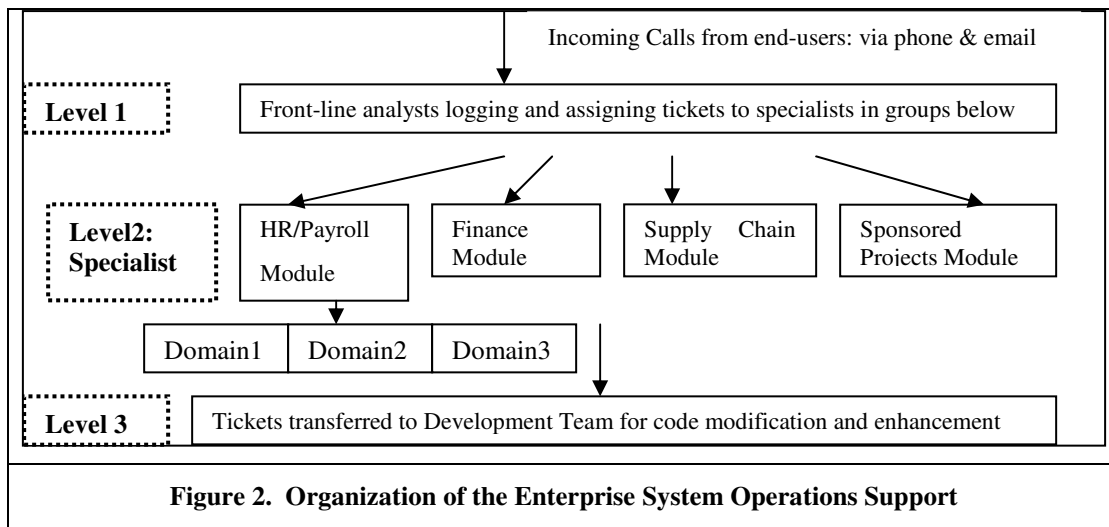
Additionally, we also conducted interviews with support center manager and specialists in December 2007 and March 2008 for additional insights about the post-implementation support context. In December 2007, eleven months after the system go-live, the first author conducted semi-structured interviews with the support center manager and two support specialists and asked them open-ended questions about their experience with post-implementation support, including the types of problems encountered by organizational end-users, support staff’s resolution strategies, and challenges in helping end-users learn to use the new enterprise system. Two more interviews were conducted in March 2008. The interviewees’ responses were written down and transcribed after the meetings. A total of five interviews were conducted. Each interview lasted forty-five to seventy-five minutes, and provided us an opportunity to enhance our understanding about the complex support environment post-implementation. Analysis of both the archival data and interview data are still on-going at the revision of this research-in-process paper.

Operation of Enterprise System Support

Employees at GiantOrg had two channels to report their system use problems: phone calls or emails. The majority of system use problems were called in, while about 25% to 30% (according to the support center manager’s estimate) of the problems were reported via e-mails. Both emailed and phoned problems were logged in the tracking system with description of the problem and contact information of the reporting employees.

There were three levels of support professionals at the Support Center: front-liner, specialist, and developer. Level 1 analyst received calls and logged them with a unique ticket number, then assigned the tickets to specialists who supported each of the four SAP modules: HR/Payroll, Finance, Supply Chain and Sponsored Projects. A specialist may be assigned to support one business domain (sub-module), such as “benefits”, on multiple domains, such as “benefits”, “personal administration”, and “payroll” (labeled as “domain1”, “domain2”, “domain3” etc in the Figure). When level 2 specialists could not resolve a problem, they passed it to the development team at level 3 for system modification and enhancement. Among all three levels of support, specialists at level 2 were the main knowledge source to directly address end-users’ SAP use problems. Thus, they became the focal IS support

professionals in this study. The following figure (Figure 2) portrays the overall organization of the SAP operations support at the research site.



Measuring and Modeling Productivity and Experience in System Support Work

Numerous studies in organizational learning have documented the link between cumulative experience and some measures of performance improvement (Argote 1999). Likewise, we argue that the “learning from doing” phenomenon also exists in professional services such as information system support. To measure productivity in this context, we use resolution time per ticket as the performance measure. As each ticket represents a customer-reported problem, we consider it a basic unit of tasks in enterprise system support. Hence, the volume of tickets resolved by a support professional becomes a direct measure of his workload, because the support work involves educating users about system features, training users to perform a business task using the system, and helping users fix the errors in system use. Since majority of IS support cost is labor cost (e.g., staff salary), we use the average resolution time (ART) per ticket to measure a specialist’s productivity. Similar measures of “labor hours per unit of work” were used in previous learning curve studies (e.g. Argote and Epple 1990) and study of technical support (Das 2003).

The base learning curve model below examines at the individual level the learning effect of specialized experience and of varied experience. To isolate the effects of cumulative experience on ticket resolution, we need to include in our model a few control variables. Consistent with prior studies (e.g., Argote, 1999), our model controls for the passage of time (e.g. month), and economies of scale (by including the total number of tickets for a given period and its squared term). We also add a control for software characteristics, such as the software module, because the software modules in SAP/R3 (HR_Payroll vs. Supply Chain) may differ in their level of difficulty and complexity.

Base Model: $\text{Ln}(\text{ART}_{it}) = \beta_0 + \beta_1 \text{tickets}_{it} + \beta_2 \text{tickets_sq}_{it} + \beta_3 \text{Month}_t + \beta_4 \text{Module}$
 $+ \beta_5 (\text{Ln}(\text{Exp_S}_{i(t-1)})) + \beta_6 (\text{Ln}(\text{Exp_V}_{i(t-1)})) + \varepsilon_{it}$, where $t = (1,12)$ months

In the base model above, $\text{Exp_S}_{i(t-1)}$ refers to the cumulative number of tickets on focal (specialized) domain resolved by individual (i) until the previous period (t-1). $\text{Exp_V}_{i(t-1)}$ refers to the cumulative number of tickets on non-focal areas resolved by individual (i) until the previous period (t-1). Since time to resolve a ticket can not decline at a linear rate, we will perform a log transformation of the variable “average resolution time (ART)” and the variable of specialized experience and of varied experience. This approach is appropriate when evidence of nonlinearity exists and researchers wish to use OLS. Four additional variables are added in the model as control variables: Tickets_{it} is defined as the total number of tickets resolved by individual i in period t . Tickets_sq_{it} is the squared term for the corresponding ticket volume. Month_t is a dummy variable for each month, e.g. $t=0$ for April 2007, $t=1$ for May 2007 etc. Module is a dummy variable for each application module. ε is the error term.

Full Model: $\text{Ln}(\text{ART}_{it}) = \beta_0 + \beta_1 \text{tickets}_{it} + \beta_2 \text{tickets_sq}_{it} + \beta_3 \text{Month}_t + \beta_4 \text{Module}$
 $+ \beta_5 (\text{Ln}(\text{Exp_S}_{i(t-1)})) + \beta_6 (\text{Ln}(\text{Exp_V}_{i(t-1)})) + \beta_7 \text{Task_L}_i * \text{Ln}(\text{Exp_S}_{i(t-1)}) + \beta_8 \text{Task_D}_i * \text{Ln}(\text{Exp_V}_{i(t-1)})$
 $+ \beta_9 \text{Network_C}_i * \text{Ln}(\text{Exp_S}_{i(t-1)}) + \beta_{10} \text{Network_B}_i * \text{Ln}(\text{Exp_V}_{i(t-1)}) + \varepsilon_{it}$, where $t = (1,12)$ months

The full model examines the moderating effect of task types (*Task_L* and *Task_D*) and of network characteristics (*Network_C* and *Network_B*) on the learning relationship. *Task_L_i* and *Task_D_i* refer to the percentage of locating tasks and percentage of diagnosing tasks respectively for individual (*i*) in period (*t*). Regarding the two network measures, *Centrality* (*Network_C*) refers to the number of tasks and the number of IS professionals the IS professional are associated with in the same domains. *Betweenness* (*Network_B*) refers to the proportion of domain-specific knowledge flows that are addressed by individuals on the IS professional's module-specific team. Both measures are based on the respective measures of degree centrality and betweenness centrality as articulated in the social networks analysis literature (Wasserman and Faust 1994).

The coefficients of the model can be interpreted as follows. β_5 captures the impact of specialized experience on time required per tickets across all support professionals on average. We expect to see a negative sign for this coefficient to evidence learning from specialized experience. Similarly, β_6 captures the impact of varied experience on time required per ticket, and is expected to show a negative sign. A significant and negative coefficient for the interaction terms (e.g., β_7 and β_9) would support our hypothesis that *specialized* experience will be more beneficial to learning outcome when a task is locating type (β_7) or when knowledge network centrality is high (β_9). Similarly, a significant and negative coefficient for the interaction terms (e.g., β_8 and β_{10}) would support our hypothesis that *varied* experience will be more beneficial to learning outcome when a task is diagnosing type (β_8) or when knowledge network betweenness is high (β_{10}). Other coefficients are for control variables. For example, β_1 and β_2 are vectors of coefficients that reflect the first and second order economies of scale.

Implications

Prior research seems to present a conflicting view on the role of IT support desk in helping users learn a new system. While some researchers (Santhanam et al. 2007) emphasize the effectiveness of IT help desk in transferring technical knowledge to organizational end-users, other scholars (e.g., Govindarajuu 2002) suggest that IT help desks failed in resolving users' problems due to lack of business domain expertise. Thus, findings of this study will offer some explanations for the inconsistent views and suggest several ways by which IS support professionals' can acquire business domain knowledge and improve their productivity.

As this study focuses on a four-site ERP implementation of a large organization with its unique organizational context, the generalizability of the research findings is likely to be constrained by the type of organizational structure. Nevertheless, our focus on individuals' involvement in peer knowledge networks highlights the significance of IS professionals' sharing of business and customer knowledge. This echoes the findings that knowledge on business, customers and project management have become increasingly important for IS professionals to survive and thrive in the dynamic environment of IT services (Gallagher et al. 2010). Moreover, this study highlights the significant role of task assignment and knowledge network with respect to the two types of experience learning (specialized vs. varied). The findings of this study will provide IS managers insights into managing effectively their human resources, such as assigning an IS staff to a specialized business area or to a specific type of tasks. Meanwhile, findings of this study will offer IS professionals useful guidance on utilizing knowledge network of peers and on developing a portfolio of skills to advance their careers in the competitive IS service profession.

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