AIS Transactions on Human-Computer Interaction

Volume 13 | Issue 2 Article 2

6-30-2021

Does Supplementing IS Analysts' User Observations With Hands-on Training Help Them Better Understand Users' Work?

Shadi Shuraida
University of Quebec, shadi.shuraida@teluq.ca

Henri Barki
HEC Montreal, henri.barki@hec.ca

Recommended Citation

Shuraida, S., & Barki, H. (2021). Does Supplementing IS Analysts' User Observations With Hands-on Training Help Them Better Understand Users' Work?. *AIS Transactions on Human-Computer Interaction, 13*(2), 145-174. https://doi.org/10.17705/1thci.00146
DOI: 10.17705/1thci.00146

Transactions on Human-Computer Interaction

Volume 13 Issue 2

6-2021

Does Supplementing IS Analysts' User Observations With Hands-on Training Help Them Better Understand Users' Work?

Shadi Shuraida

TELUQ - University of Quebec, shadi.shuraida@teluq.ca

Henri Barki

Retired from HEC Montréal, henri.barki@hec.ca

Recommended Citation

Shuraida, S. & Barki, H. (2021). Does Supplementing IS Analysts' User Observations With Hands-On Training Help Them Better Understand Users' Work? *AIS Transactions on Human-Computer Interaction*, *13*(2), pp. 145-174.

DOI: 10.17705/1thci.00146

Available at http://aisel.aisnet.org/thci/vol13/iss2/2

Transactions on Human-Computer Interaction

Research Paper DOI: 10.17705/1thci.00146 ISSN: 1944-3900

Does Supplementing IS Analysts' User Observations With Hands-on Training Help Them Better Understand Users' Work?

Shadi Shuraida
School of Business Administration, TELUQ - University of Quebec

Henri Barki
Department of Information Technologies, HEC Montreal (Retired)

Abstract:

IS analysts need to acquire knowledge about users' work processes to design high-quality systems. While researchers have proposed hands-on activities in cognitive learning theories to improve knowledge acquisition, current approaches rely on analysts verbally communicating with users or observing them perform their tasks in order to learn these work processes. We draw on social cognitive theory (SCT) to hypothesize and examine how effectively two learning approaches (an observation-only approach and an observation plus hands-on approach) help analysts better understand users' computer-mediated work processes. Accordingly, we conducted an experimental study to compare these two learning approaches. We found that, while participants who had low prior domain knowledge about users' work processes ended up understanding them better in the observation plus hands-on treatment than in the observation-only treatment, the difference between the two approaches was not significant for participants who had high prior domain knowledge.

Keywords: IS Analyst Learning, Knowledge Structures, Social Cognitive Theory, IS Development

Richard Johnson was the accepting senior editor for this paper.

1 Introduction

While the recognition that analysts need to understand users' system needs has resulted in much literature that focuses on improving their ability to elicit system requirements (for a review, see Mathiassen, Saarinen, Tuunanen, & Rossi, 2007; Méndez Fernández et al., 2017), evidence in the literature suggests that, even when analysts acquire all the necessary user requirements, they still may not be able to recognize users' fundamental issues, which can result in systems that fail to meet users' needs (Gallivan & Keil, 2003; Markus & Mao, 2004; Shuraida & Barki, 2013). According to a report from the Standish Group (2015), inaccurate or inadequate system features negatively impact more than two thirds of IS projects and result in poor system quality, project delays, and cost overruns. Accordingly, researchers and practitioners have both underscored the idea that, in order to develop better systems, IS analysts need to better understand users' work processes and the application domain[1] that a future system intends to support (Beyer & Holtzblatt, 1995; Byrd, Cossick, & Zmud, 1992; Schenk, Vitalari, & Davis, 1998; Vitalari, 1985).

Some IS scholars have suggested that analysts need to observe users perform their tasks in order to better understand their work processes (e.g., Beyer & Holtzblatt, 1995; Dennis, Wixom, & Tegarden, 2015; Satzinger, Jackson, & Burd, 2016); that is, that they need to use observational learning[2] methods. These methods build on social cognitive theory (SCT), a dominant paradigm in learning (Robertson, 1990; Taylor, Russ-Eft, & Chan, 2005) and IT training research. Findings from studies on these methods in which users first observe a model and then re-enact the behaviors (Gupta, Bostrom, & Huber, 2010; Santhanam, Sasidharan, & Park, 2013, p. 143) have consistently "converge[d] on the[ir] superiority".

The IT-training literature provides considerable insights into how participants learn computer applications (Gupta et al., 2010; Santhanam et al., 2013). We can extend this literature in two ways in order to better inform analysts when they learn about users' computer-mediated work processes. First, while this literature has focused on participants learning productivity software (Gupta et al., 2010; Santhanam et al., 2013), analysts often need to learn users' work tasks that they often conduct using more complex systems, such as enterprise systems. Second, although this literature has largely focused on novice users learning a new system (Gupta et al., 2010), analysts often design systems in familiar and novel domains throughout their careers as external consultants, agile experts, or organizational employees (Ko, Kirsch, & King, 2005; Schenk et al., 1998; Vitalari, 1985). Indeed, past research suggests that the benefit of certain observational learning approaches to the learner may depend on the learner's prior domain knowledge. Notably, despite the central role that hands-on activites play in SCT for learning complex tasks (Johnson & Marakas, 2000; Gupta et al., 2010), researchers have found mixed results for the value it adds to observation (for a review, see Robertson, 1990; for a meta-analysis, see Taylor et al., 2005) and suggested that its influence may depend on a learner's prior knowledge and expertise about the domain (Tannenbaum & Yukl, 1992; Taylor et al., 2005).

The above considerations suggest that it would be useful to consider analysts' domain knowledge when empirically examining whether hands-on observational learning approaches can help them better understand users' work processes. In order to expand our knowledge on this issue, we conducted an experiment with 43 participants in order to compare how effectively observation-only and observation plus hands-on activities help analysts learn about users' work processes that they perform when using an enterprise system. We found that participants who had low prior domain knowledge benefited more from the observation plus hands-on treatment than from the observation-only treatment, and that the difference between two approaches lacked significance for participants who had high prior domain knowledge.

[1] Consistent with Iivari, Hirschheim, and Klein (2004), we use the term "application domain" (or domain) to refer to a domain such as accounting, logistics, or marketing in which an organization currently or will use an IS. As the term "work processes" refers to the activities that users perform in an organizational context in order to produce products and/or services (see Alter, 2001; Iivari et al., 2004), we use "application domain knowledge" (or domain knowledge) in order to refer to general knowledge regarding a given domain's concepts and principles and "work process knowledge" to refer to specific knowledge of the organizational activities that users perform to make products and/or services.

[2] According to social cognitive theory (SCT), observing and modeling competent models represent observational learning's foundation. However, according to Bandura (1988, 1999), effective observation and modeling provide guidance and feedback for explaining the rules that underlie a performed behavior, and the empirical literature we mention in this paper has used this "guided observation/modeling" approach.

2 Conceptual Background

Contemporary systems analysis and design practices suggest that "more than any other activity, observing a business process in action" will help analysts better understand users' processes (Satzinger et al., 2016, p. 56; Dennis et al., 2015). According to social cognitive theory (SCT), observation constitutes the first of two information processing activities that constitute observational learning. More specifically, SCT suggests that learning starts with behavior modeling in which individuals transform information about an observed behavior into knowledge structures that represent the "*models, rules, and strategies*" underlying that behavior (Bandura, 1986; Bandura, 1999, p. 24, italics added). Subsequently, in enactive mastery, learners refine and correct these knowledge structures as they perform the behavior themselves (i.e., by engaging in hands-on activities) (Bandura, 1986; Bandura, 1999).

Notably, SCT has been the prevalent theory in IT learning and training research, which has found observational learning to be more effective than other learning methods (for useful reviews, see Gupta et al., 2010; Santhanam et al., 2013). However, this research has largely focused on novice participants using observation to learn productivity software (Gupta et al., 2010) and paid little attention to hands-on activities' additional learning effects. While some researchers have found hands-on (enactive learning) activities to provide attentional and feedback mechanisms that enhance and refine learners' knowledge (Bandura, 1999), previous empirical research has not clearly established their benefit to observation (for a review, see Robertson, 1990; for a meta-analysis, see Taylor et al., 2005). The few IT training studies that have examined hands-on activities' additional knowledge benefit (to observation) have found similar mixed results (see Gupta & Bostrom, 2013; Yi & Davis, 2001).

Some researchers suggest that the value that hands-on practice provides to observational learning may depend on a learner's prior domain knowledge (Yi & Davis, 2001; Tannenbaum & Yukl, 1992; Taylor et al., 2005). As such, we need more research that considers analysts' expertise and learning processes given the little work on the topic in the IT training and learning literature (Gupta et al., 2010). Accordingly, in this paper, we extend SCT in two main ways. First, we draw on the cognitive learning literature to account for the influence that prior domain knowledge has on individuals' learning (Anderson, 1982; Glaser, 1990). Whereas SCT specifies the role that prior experience has on motivational and regulatory processes, such as outcome expectations and self-efficacy (Bandura, 1986), the cognitive learning literature expands on the influence that prior knowledge has on learning. Second, SCT provides a conceptual framework that illustrates how individuals develop behaviors and competencies (Bandura, 1986). However, analysts need to learn users' work processes to design systems rather than competently perform these processes themselves. As such, we include the notion of knowledge structure in order to examine individuals' understanding of the learned concepts and their relationships.

2.1 Analyst Learning and Expertise

Cognitive learning researchers agree that one's knowledge acquisition involves a transition from possessing encoded declarative knowledge (i.e., general knowledge about facts, concepts, and principles in a domain, such as accounting or logistics) to acquiring more interconnected and organized "chunks" of knowledge that define the rules and relationships between these concepts (i.e., knowledge structure) (Anderson, 1982; Bandura, 1999; Glaser, 1990).

Researchers have observed that experts and novices differ more in their knowledge structures than their declarative knowledge (Day, Arthur, & Gettman, 2001; Kraiger, Ford, & Salas, 1993) and that more developed knowledge structures reflect an individual's domain expertise (Dorsey, Campbell, Foster, & Miles, 1999; Glaser, 1990; Rowe, Hall, Cooke, & Halgren, 1996). Further, researchers have found these knowledge structures to be more important than declarative knowledge for how effectively one accomplishes tasks, recalls information, solves problems (Day et al., 2001; Dorsey et al., 1999; Kozlowski et al., 2001; Rowe et al., 1996), acquires new information (Glaser, 1990; Kraiger et al., 1993), and understands complex and ill-defined domains (Day et al., 2001; Rowe et al., 1996).

The IS literature echoes these findings and suggests that having accurate knowledge structures of users' work processes likely helps analysts infer relations between various abstract, and often complex concepts about users' work processes and application domains (Huang & Burns, 2000; Mackay & Elam, 1992; Schenk et al., 1998). Analysts likely first develop these knowledge structures via acquiring declarative knowledge, which then becomes increasingly structured through mental and physical practice. Consequently, analysts can draw on their knowledge structures in order to accomplish various system-development tasks to create physically representations of an IS and its related work processes (Browne & Parsons, 2012).

Hence, given that analysts focus on designing systems that meet users' task needs rather than skillfully perform these tasks themselves, we use knowledge assessments that focus on analysts' cognitive knowledge of users' work. More specifically, as we summarize in Table 1, we evaluate analysts' knowledge of users' work processes via their a) declarative knowledge, b) knowledge structure, and c) conceptual models. These components closely correspond to knowledge types that previous IT learning studies have proposed (Gupta et al., 2010; Nambisan, Agarwal, & Tanniru, 1999; Santhanam, Seligman, & Kang, 2007). In the present study, while declarative knowledge closely corresponds to know-what that reflects analysts' knowledge of work process concepts and task procedures, knowledge structures and conceptual models closely correspond to know-why, which reflect analysts' knowledge of the rules and interrelatedness between work process concepts. For example, in order to develop an appropriate supply chain system, analysts need to understand the product inventory concept and recognize that a replenishment operation occurs once inventory falls below a certain level (business concept and procedural know-what). They also need to understand the interrelationship between this concept and other work process concepts, such as product sales, forecast, and pricing (know-why).

Table 1. The Knowledge Concepts We Use in this Study

Concept	Definition	Conceptualization in previous studies	Conceptualization in the present study
Declarative knowledge	"Knowledge about facts, concepts, and principles that apply within a certain domain" (de Jong & Ferguson-Hessler, 1996, p. 107).	Know-what: "conceptual knowledge of the system functions and which of these are useful to support business tasks" (Santhanam et al., 2007, p. 176)	Analysts' knowledge about users' work process concepts and tasks that an ERP system supports.
Knowledge structures	"Knowledge of how concepts within a domain are interrelated and organized" (Jonassen, Beissner, & Yacci, 1993, p. 4).	Know-why: "knowledge of the business rules built into the systems" (Santhanam et al., 2007, p. 177).	Analysts' knowledge of the organization, interrelatedness, and rules that underlie users' work process concepts and tasks.
Conceptual models	"[Conceptual models] represent the semantics of the domain as perceived by stakeholders of the information system" (Burton-Jones, Wand, & Weber, 2009, p. 496)	Know-why: "knowledge of the business rules built into the systems" (Santhanam et al., 2007, p. 177).	Analysts' formal semantic representation of the relationships and rules that underlie users' work processes and tasks.

2.2 Analysts' Prior Domain Knowledge and Learning Methods

Social cognitive theory (SCT) posits that learners develop knowledge structures about behaviors via observation and that they further develop these structures as they model the behaviors or perform them themselves (Bandura, 1999). Cognitive learning research has supported these ideas and suggested that hands-on experience can help develop knowledge structures via two mechanisms: 1) experimenting with an activity can provide learners direct feedback that can enable them to identify problems and evaluate their hypotheses regarding that activity (Bell & Kozlowski, 2008; Frese et al., 1988) and can allow them to make mistakes, which, in turn, can help them develop integrated and coherent knowledge structures (Frese et al., 1988; Keith & Frese, 2008); and 2) hands-on activities can lead to greater attention and motivation than vicarious learning methods, such as observation alone (Bell & Kozlowski, 2008; Frese et al., 1988).

However, while hands-on practice will likely provide added benefit to novice learners, it will not likely benefit experts for two reasons. First, while novices often tend to overestimate their knowledge (Kruger & Dunning, 1999; Johnson & Marakas, 2000) and will likely require the direct feedback from hands-on experience that allows them to validate their knowledge and correct any misconceptions and knowledge gaps they have (Yi & Davis, 2001), experts are more aware of their knowledge abilities (Johnson & Marakas, 2000) and more likely to better address them via observation alone. Second, as novices have greater knowledge gaps and less integrated and structured knowledge (Huang & Burns, 2000), they will likely require additional cognitive effort and hands-on experience to acquire knowledge about a particular domain. In contrast, experts' well-organized knowledge structures enable them to more easily process and acquire novel and unstructured information about that domain (Huang & Burns, 2000; Sweller, 1988). Thus, once experts have assimilated the information they acquire from observation into their knowledge structure, providing redundant information fails to deliver any learning gains (Kalyuga, 2007).

The above considerations suggest that, by first observing users demonstrate their work, a novice analyst who possesses little prior knowledge regarding that user's domain would be able to understand the concepts involved in that user's work process and the relationships among those concepts at a basic level (i.e., develop their own knowledge structures of the users' work process). Then, by performing these activities hands-on, analysts who possess low prior domain knowledge (novice) would be likely to better integrate and organize their newly learned concepts, and, through a trial-and-error process, they would be able to better organize and develop the relationships between them. In contrast, by observing users execute their work processes, analysts who already have prior domain knowledge about users' work domain (e.g., expertise in accounting, operations) would be likely to more easily acquire and integrate new and relevant knowledge into their existing knowledge structures than analysts who possess little prior domain knowledge. As such, "already knowledgeable or expert" analysts would be less likely to benefit from doing additional hands-on activity since such activity would likely provide redundant knowledge. Hence, we hypothesize:

H1: The observation plus hands-on approach positively influences the accuracy of analysts' knowledge structure (concerning users' work processes) more strongly than the observation-only approach when they have low prior domain knowledge (concerning the general domain of those work processes) compared to when they have high prior domain knowledge.

H1 compares the interaction between both learning approaches and analysts' prior domain knowledge. Interestingly, the above argument also suggests that an observation-only approach will more strongly benefit analysts who have high prior domain knowledge than analysts who have low prior domain knowledge. This reasoning suggests that, just by observing users demonstrate their work processes, analysts who have high prior domain knowledge would be likely to more easily acquire and integrate new and relevant knowledge (e.g., about a specific work process in an organization) into their existing knowledge structures than analysts who have low prior domain knowledge. Hence, we hypothesize:

H2: In an observation-only approach, analysts with high prior domain knowledge accumulate more accurate knowledge structures of users' work processes than analysts with low prior domain knowledge.

Even though knowledge structures represent analysts' cognitive models about users' work processes (Bandura, 1986), analysts also need to use formal modeling approaches in order to communicate their application domain and work process knowledge to users and other project stakeholders (Browne & Parsons, 2012; Davern, Shaft, & Te'eni, 2012; Wand & Weber, 2002). As such, we also need to measure IS analysts' conceptual models and declarative knowledge to examine their IS design effectiveness (e.g., Khatri, Vessey, Ramesh, Clay, & Park, 2006; Marakas & Elam, 1998). Yet, while researchers believe that analysts rely on internal mental representations to create such physical models, they have yet to extensively examine these models' quality and how well they represent their knowledge of work processes (Davern et al., 2012, p. 278; Khatri & Vessey, 2016).

In order to create physical artifacts that model "real-world" work process concepts and their relationships, analysts need to draw on their internal representations (Davern et al., 2012; Wand & Weber, 2002) (i.e., their knowledge structures). Given that well-structured knowledge can help enhance information retrieval and recall (Chi, Glaser, & Rees, 1982; Glaser, 1990; Kraiger et al., 1993), analysts with more developed knowledge structures will be more likely to recall work process concepts and their relationships and, thus, more likely to render more complete and accurate conceptual models. Hence, we hypothesize:

H3: The accuracy of IS analysts' knowledge structures of users' work processes positively influences the accuracy of their conceptual models (of users' work processes).

Further, given that structured knowledge facilitates information recall and recognition (e.g., Chi et al., 1982; Davis & Yi, 2004), as analysts' knowledge of users' work processes becomes more structured, they will be more likely to more effectively recall their declarative knowledge about those processes. Hence, we hypothesize:

H4: The accuracy of IS analysts' knowledge structures of users' work processes positively influences the accuracy of their declarative knowledge of those processes.

3 Method

In order to test the above hypotheses, we conducted an experiment by manipulating learning as a between-subject factor and randomly assigning subjects to one of the following two treatments: 1) observation only, and 2) observation plus Hands-on.

3.1 Participants

We recruited students in graduate management information systems (MIS) programs, graduate computer science (CS) programs, or masters of business administration programs with an IS background or IS concentration from four universities. First, we conducted a pre-test and a pilot study (with two and 17 participants, respectively) to assess and improve the experimental procedure and study measures. Next, we conducted the experiment with 51 graduate students who had agreed to participate in the study. However, we eliminated eight due to their self-assessed language deficiency, which yielded a final sample with 43 participants (16 MBA, 11 MIS, and 16 CS students). We describe participants' characteristics in Table 2 below.

Table 2. Participant Characteristics

<table>
<tr><th rowspan="2">Demographics</th><th rowspan="2">Category</th><th colspan="2">Participants in each category</th></tr>
<tr><th>Count</th><th>%</th></tr>
<tr><td rowspan="3">Participants' degree (completed or pending)</td><td>MBA</td><td>16</td><td>37.2</td></tr>
<tr><td>Management information systems</td><td>11</td><td>25.6</td></tr>
<tr><td>Computer science</td><td>16</td><td>37.2</td></tr>
<tr><td rowspan="5">Years of IT-related work experience
Mean: 4.26 years
Standard deviation: 3.61 years</td><td>< 1 year</td><td>5</td><td>11.6</td></tr>
<tr><td>1 - 4 years</td><td>21</td><td>48.8</td></tr>
<tr><td>5 - 8 years</td><td>12</td><td>27.9</td></tr>
<tr><td>9 - 12 years</td><td>3</td><td>7.0</td></tr>
<tr><td>> 12 years</td><td>2</td><td>4.7</td></tr>
<tr><td rowspan="7">Type of IT-related work experience (numerous participants had multiple experiences)</td><td>Software application programming/development</td><td>34</td><td>79</td></tr>
<tr><td>System/business analysis</td><td>23</td><td>53</td></tr>
<tr><td>IS project management</td><td>18</td><td>42</td></tr>
<tr><td>Database administration</td><td>13</td><td>30</td></tr>
<tr><td>Network security administration</td><td>6</td><td>14</td></tr>
<tr><td>Network architecture/administration</td><td>11</td><td>26</td></tr>
<tr><td>Other (e.g., IT support and QA)</td><td>15</td><td>35</td></tr>
<tr><td rowspan="4">Experience gathering requirements during IS projects (number of projects)</td><td>None</td><td>17</td><td>39.5</td></tr>
<tr><td>1-4 projects</td><td>22</td><td>51.2</td></tr>
<tr><td>5-8 projects</td><td>2</td><td>4.7</td></tr>
<tr><td>> 8 projects</td><td>2</td><td>4.7</td></tr>
<tr><td rowspan="4">Age group (years)</td><td>20-25</td><td>13</td><td>30.2</td></tr>
<tr><td>26-30</td><td>16</td><td>37.2</td></tr>
<tr><td>31-35</td><td>9</td><td>20.9</td></tr>
<tr><td>36-40</td><td>5</td><td>11.6</td></tr>
<tr><td rowspan="2">Gender</td><td>Male</td><td>35</td><td>81</td></tr>
<tr><td>Female</td><td>8</td><td>19</td></tr>
</table>

As the table shows, the participants had highly similar profiles to the professional IS analyst population (U.S. Department of Labor, 2013). In fact, several had already worked as professional IS analysts. The participants had 4.3 years of various IT-related work experience on average, 53 percent had worked as system/business analysts, and approximately 60 percent had experience in collecting system requirements in their respective IT functions[3]. Note that the participants' similarity to IS analysts diminishes any potential issues regarding the student sample's external validity and generalizability (Compeau, Marcolin, Kelley, & Higgins, 2012; Gordon, Slade, & Schmitt, 1986).

3.2 Experimental Task

The learning goal was for the participants to learn how a firm that distributes bottled water operates and to use the mySAP ERP package (which we refer to as SAP henceforth) to manage its operations. The package comes with ERPsim, software that simulates a buyer and supplier market and the passage of time. It also automates several administrative SAP transactions (Léger, 2006). ERPsim simulates a "real-world" operational business context that participants can use to evaluate the impact of their decisions across time (we describe ERPsim in more detail in Appendix A). In the experimental simulation, participants used the SAP interface to execute transactions and view reports in exactly the same way that one would use SAP in an actual organization. The experiment used a work process that comprised buying and selling bottled water. Thus, in addition to learning transactions to perform different SAP activities, the participants had to also identify the information that the system provided in order to make operational decisions. No participant had any prior experience with ERPsim or with the experimental work process.

3.3 Experimental Procedure

The experimental procedure used a randomized block design with subgroups that represented the participants study area (MBA, MIS, or CS) in order to minimize any potential differences between subgroup characteristics. We randomly assigned the participants from each block to one of two conditions: 1) observation only or 2) observation plus hands-on. As Figure 1 shows, all participants followed a similar experimental procedure except the participants in the treatment manipulation. Each participant conducted the experimental procedure individually in an office. First, we told them that we conducted our study to investigate how IS analysts learn users' tasks, but we did not tell them about the different conditions. Next, asked them to respond to a pre-treatment questionnaire on demographic data (age group, educational background, IS-related experience, systems analysis experience, SAP and other ERP package experience, English proficiency, and prior knowledge of the task's knowledge domain (i.e., operations management and logistics)). We explain how we developed the domain knowledge questions in Appendix B.

Subsequently, we informed the participants that we would show them a task that simulated a real-life context after which we would ask them some questions about it. Next, we showed them a pre-recorded presentation that described the organizational context, which included organization's products, operations, and market environment. Finally, the participant performed one of the two experimental treatments and, when finished, completed a post-treatment questionnaire that contained a declarative and structural knowledge test and a conceptual modeling task. The experimental session lasted approximately two hours for each participant. The study facilitator and research assistant (MIS doctoral students) followed a detailed script to ensure procedural consistency for each participant, and the facilitator observed each participant throughout the procedure in order to ensure their adherence to the treatment procedure.

Further, in order to encourage participants to better focus on their experimental task, we paid them CAD$60 for their time plus an additional payment of up to CAD$25 depending on their knowledge-assessment score that we calculated at the end of the experimental session.

[3] We note that the relatively small proportion of female participants in the study sample resembles the percentage of females who major or work in the IS/IT field, which ranges from 20 to 30 percent (Armstrong, Riemenschneider, & Giddens, 2018; U.S. Department of Labor, 2013; Harris, Cushman, Kruck, & Anderson, 2009).

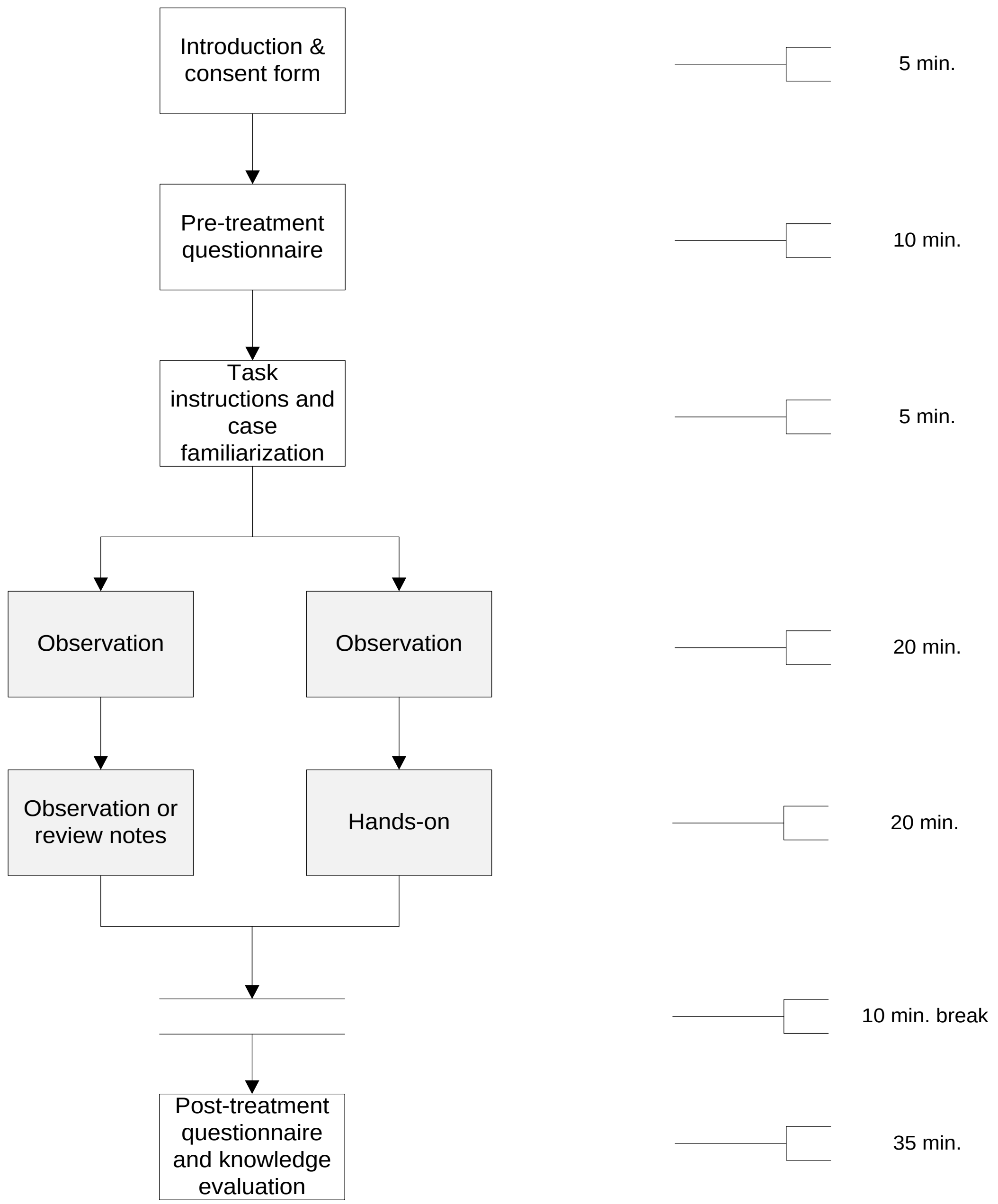

Figure 1. Experimental Procedure

3.4 Experimental Treatment Design

In order to simulate a real-world analyst-user interaction environment, we followed applied ethnography approaches (Ball & Ormerod, 2000) and contextual inquiry (Beyer & Holtzblatt, 1995) that human-computer interaction and design research uses (Ball & Ormerod, 2000; Millen, 2000) to model the treatment's observation component. Specifically, all participants watched a pre-recorded video of a research assistant who played a business expert. We told them that, in their role as system analysts, they needed to learn the work process they were about to observe in the video. During their session, each participant could also pause the video and ask questions to the research assistant (who stayed with the participant throughout this phase) whenever they wanted. We trained and instructed the research assistant to confine his answers and explanations only to task procedures and processes, and the assistant could repeat or further explain any part if a participant asked. We tested how consistently the research assistant responded to participants via 17 pilot sample interviews. In order to control for any potential confounding effects from different assistants, the same assistant acted as the expert in all interviews.

Following the video observation, we encouraged participants in the observation-only treatment to review their notes, re-watch any video segment, or ask questions to the assistant in case they finished the interview before the end of the allotted time. However, during the second half of the experimental session, rather reviewing their notes or re-watching video segments like the participants in the observation-only treatment, we asked the participants in the observation plus hands-on treatment to use SAP for 20 minutes in order to manage the firm's operations and maximize its profitability. We based the model we used for this hands-on treatment on previous studies that have used exploratory research with few instructions about task procedures (e.g., Bell & Kozlowski, 2008; Carroll, Mack, Lewis, Grischkowsky, & Robertson, 1985; Frese et al., 1988). However, the model also provided participants with an objective and, thus, guidance to help focus their activities (Bell & Kozlowski, 2008). Also note that the same research assistant assisted participants during the hands-on experimental phase to provide help about software procedures and use.

3.5 Measures

We assessed participants' knowledge of users' work processes via declarative and structural knowledge measures and a conceptual modeling task.

3.5.1 Declarative Knowledge

We measured declarative knowledge at the end of each experimental session via 13 multiple-choice and true/false questions (we provide examples in Appendix C) that assessed the amount of knowledge each participant retained about task concepts and procedures. As no knowledge measures existed for the experimental task, we followed a deductive approach to create 10 questions to assess how well the participants recalled terms and activities related to their task. In developing these questions, we considered the ERPsim training materials and ensured we came to a consensus before we pre-tested them with two PhD students who were familiar with the experimental task and with the 17 participants in the pilot study. Based on their feedback, we revised some items for greater clarity, which also resulted in our adding three new items. We calculated each participant's declarative knowledge score as the number of correct answers they gave to the 13 questions.

3.5.2 Knowledge Structure

We measured knowledge structure via a structural assessment approach that involved knowledge elicitation, representation, and evaluation (Goldsmith, Johnson, & Acton, 1991). In order to elicit how well participants understood relationships between task concepts, we identified the key concepts that represented the task domain. As no empirically validated procedures existed for selecting task concepts, we followed the suggestions in past research on cognitive structures in order to identify and refine relevant knowledge structure concepts. Thus, as researchers knowledgeable about the ERPsim tasks, we identified a list of 13 task-central concepts that a panel of three subject-matter experts (i.e., the researchers who designed the simulation software and the study's experimental task) subsequently reviewed and revised. Based on the experts' suggestions, we deleted one concept and made minor revisions to the others. As Appendix D shows, we then used the final set of concepts to ask respondents to assess the relatedness between each concept pair on 10-point scales (1 = completely unrelated to 10 = highly related) based on the knowledge they had acquired about the experimental task's specific work processes[4]. Consistent with past research (Goldsmith, Johnson, & Acton, 1991), we asked the participants to base their answers on how they first intuitively judged the relatedness between each concept pair, and they all completed the rating task in the allotted time.

While the proximity matrix that the participants generated in their responses reflects their domain knowledge, this raw proximity data contains noise; thus, researchers recommend that one conduct a scaling procedure to represent the data's underlying organization (Goldsmith et al., 1991). One can do so via multi-dimensional scaling (MDS) to compute "coordinates for a set of points in a space such that the distances

[4] Note that the pre-treatment questionnaire assessed analysts' prior domain knowledge at a general abstraction level. In contrast, analysts' knowledge structures that we elicited in the post-treatment questionnaire specifically pertained to the work processes they had learned (i.e., they pertained to the specific context). Hence, analysts' prior domain knowledge differed in abstraction level than their knowledge structures. In addition, empirical studies in cognitive psychology have observed the notion that "different levels…of knowledge exist in a domain of interest" and that context-specific training mainly influences context-specific knowledge rather than general-level knowledge (e.g., Dorsey et al., 1999, p. 54).

between pairs of these points fit as closely as possible to measured dissimilarities between a corresponding set of objects" (Kruskal, 1964; Wilkinson, 1986).

Based on the above suggestion, we used MDS to assess each participant's knowledge representation by comparing it to the referent structure of the subject-matter expert panel. We correlated each participant's MDS spatial representation (Euclidian distances between concept pairs) with an average composite of experts' MDS spatial representation[5] based on the idea that "experts' organization and comprehension of domain knowledge are a close approximation of the true representation of that domain" (Day et al., 2001, p. 1023) and that experts' aggregated responses can provide a robust referent structure (Day et al., 2001). The three ERPsim developers constituted the study's expert panel and completed the structural assessment measure that we show in Appendix D. As their structural assessment largely converged (correlations between the three experts were $r_{12} = 0.65$, $r_{13} = 0.76$, $r_{23} = 0.75$, $p < 0.01$), we averaged their responses in order to provide the referent expert structure. We discuss the knowledge structure assessment in more detail in Appendix D.

3.5.3 Conceptual Model

For the conceptual modeling task, we asked participants to create a matrix similar to a modified version of an activity-data matrix[6] (see Appendix E). Similar to data-flow diagrams (DFDs), this matrix has a functional perspective as it depicts the activities performed and the data (information) flows related to those activities (Curtis, Kellner, & Over, 1992; Luo & Tung, 1999). Its three columns identify: 1) activities, 2) information input needed to perform them, and 3) their information output. We also provided participants with a list of relevant and irrelevant elements (see Appendix E) as a memory aid to help them use a consistent terminology in their matrices. We obtained the correct matrix solution from the educational literature on ERPsim, which the simulation software's technical developer verified. We then compared each participant's matrix to this solution and calculated the participant's score by giving a point for each accurate element (maximum score = 27).

4 Analyses and Results

We provide the correlations between the experimental variables in Table 3. In Table 4, we show the participants' work experience, IS analysis work experience, and prior SAP, ERP and domain knowledge. In the latter table, one can see the experimental groups did not significantly differ in any characteristic. We determined the participants' prior domain knowledge (i.e., operations management and logistics) in the pre-treatment questionnaire with a median split identifying the high and low prior domain knowledge (domain novice/expert) groups.

We tested the direct and moderating effects of participants' prior domain knowledge measures separately for H1 and H2 by calculating each participant's prior domain knowledge scores (i.e., the operations and logistics domain) as being either higher or lower than the sample median. Hence, we tested H1 with a two-way ANOVA of learning method (observation-only, observation plus hands-on) and prior domain knowledge (high, low). Table 5 provides the descriptive statistics of the analysis, and Table 6 provides the results from the two-way ANOVA.

As Table 6 shows, we found a significant interaction effect between the learning approach used and prior domain knowledge ($F(1, 39) = 7.06$, $p = .011$), which supports H1.

[5] As Appendix F shows, an elbow criterion test provided a two dimensional MDS solution with the best structural fit to the experts' concept-similarity data. Hence, we performed all subsequent MDS analyses with two dimensions.
[6] Initially, we required pilot participants to construct a DFD after a 10-minute refresher on DFD concepts. We tested their knowledge in the pre-treatment questionnaire. However, consistent with anecdotal and research findings (for a discussion, see Neill & Laplante, 2003; Wand & Weber, 2002), pilot participants found conceptual modeling difficult and could not construct a DFD. We then examined several alternative assessment approaches with other pilot participants and, based on the participants' performance, used the modified activity-data matrix rather than the DFD. The feedback from the pilot participants confirmed that the final version of this matrix (see Appendix E) did not require complex conceptual modeling skills, which reduced this factor's potential noise effect.

Table 3. Correlations Between Study Variables

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Declarative knowledge	10.09	2.39	1.00								
2. Knowledge structure	.35	.22	*0.37**	1.00							
3. Total work experience (years)	4.26	3.60	0.05	-0.00	1.00						
4. IS analysis experience (years)	1.07	1.32	-0.15	-0.18	*0.45***	1.00					
5. SAP prior knowledge	0.99	1.29	0.14	0.11	0.01	-0.18	1.00				
6. ERP prior knowledge	1.65	2.88	-0.02	0.10	0.13	*0.30**	0.16	1.00			
7. Prior domain knowledge	2.23	1.00	*0.38**	0.28	-0.23	-0.29	*0.34**	-0.05	0.25		
8. Age	28.55	5.13	-0.04	0.10	*0.55***	0.25	-0.20	*0.30**	0.20	1.00	
9. Conceptual model	15.03	5.14	*0.53***	*0.32**	-0.07	-0.18	0.15	0.18	*0.35**	-0.02	1.00
* p < 0.05, ** p < 0.01											

Table 4. Characteristics of Participants in the Observation-only and Observation plus Hands-on Treatments

	Observation only		Observation + hands-on		T-test
	Mean	S.D.	Mean	S.D.	
Total work experience	4.04	3.32	4.51	3.98	t(41) = -0.43, p = 0.67 (ns)
IS analysis experience	1.09	1.41	1.05	1.23	t(41) = 0.09, p = 0.93 (ns)
Prior SAP knowledge	0.99	1.24	0.98	1.38	t(41) = 0.01, p = 0.99 (ns)
Prior ERP knowledge	1.17	2.70	2.20	3.05	t(41) = -1.17, p = 0.25 (ns)
Prior domain knowledge	2.43	0.95	2.00	1.03	t(41) = 1.45, p = 0.16 (ns)

Table 5. Descriptive Statistics (Dependent Variable: Knowledge Structure Accuracy)

Treatment	Knowledge level	Mean	Std. Deviation	N
Observation only	Low	0.1463	0.17501	10
	High	0.4600	0.15769	13
	Total	0.3236	0.22665	23
Observation plus hands-on	Low	0.3938	0.19242	13
	High	0.3786	0.28533	7
	Total	0.3885	0.22170	20
Total	Low	0.2862	0.22014	23
	High	0.4315	0.20737	20
	Total	0.3538	0.22408	43

Table 6. Interaction Between the Learning Approach (Observation-only and Observation plus Hands-on) and Prior Domain Knowledge (i.e., Operations and Logistics)

Source	Type III sum of squares	Df.	Mean square	F	Sig.
Corrected model	0.602[a]	3	0.201	5.195	0.004
Intercept	4.792	1	4.792	124.025	0.000
Treatment (learning approach)	0.070	1	0.070	1.799	0.188
Prior domain knowledge	0.224	1	0.224	5.809	0.021
Treatment * prior domain knowledge	0.273	1	0.273	7.059	**0.011**
Error	1.507	39	0.039		
Total	7.492	43			
Corrected total	2.109	42			
R-square = 0.286 (adjusted R-square = 0.231)					

While the results in Table 6 indicate a significant interaction effect, they do not reveal its pattern. Thus, in order to identify the exact interaction pattern, we examined the effect that the two learning method treatments had (observation only and observation plus hands-on) on participants' knowledge structures for the high and low prior domain knowledge groups. As Figure 2, Table 5, and the difference of means between groups (t-tests below), participants who had low levels of prior domain knowledge acquired significantly more accurate knowledge structures in the observation plus hands-on treatment (M = 0.39, SD = 0.19), than those who were in the observation-only treatment (M = 0.15, SD = 0.18) t (21) = -3.178, p = 0.005). On the other hand, for the high prior domain knowledge group, we found no significant difference between the two learning approaches in terms of their influence on participants' knowledge structure accuracy (t (18) = 0.831, p = 0.417). Also note that, since we observed no significant differences between the low prior domain knowledge participants in the two experimental groups (in terms of their work experience, systems analysis experience, SAP/ERP knowledge, and age), these factors did not likely confound the observed and significant interaction effect (Table 7, t-test 1 vs. 2). We also measured other potentially confounding variables that we found in the literature, such as participants' self-efficacy (Johnson & Marakas, 2000) and perceived system ease of use (PEOU). We measured the variables in the post-treatment questionnaire using four items each with the former adapted from Ortiz de Guinea and Webster (2011) and the latter from Venkatesh (2000). As Table 7 shows, both intergroup t-tests did not have a significant effect on both variables.

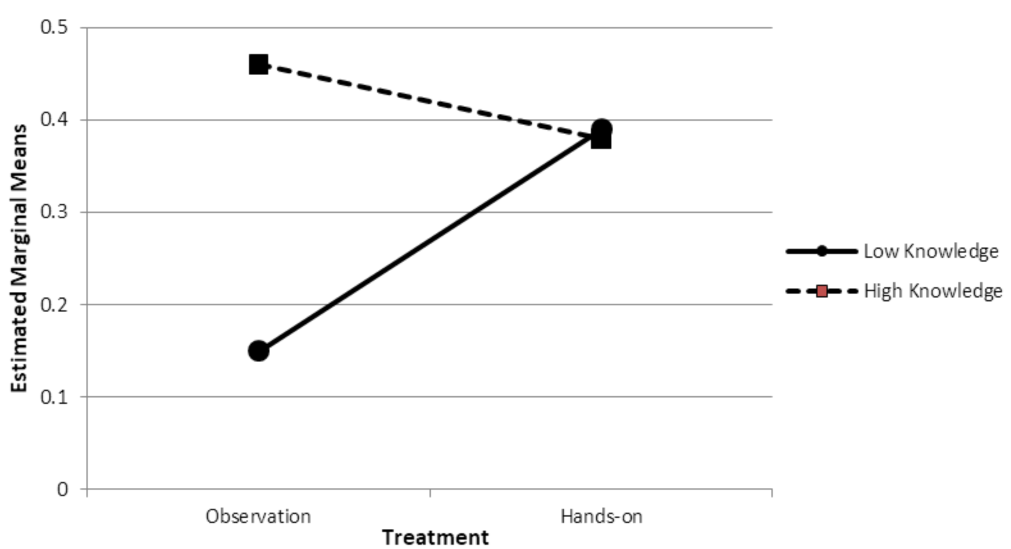

Figure 2. Knowledge Structures of High and Low Domain Knowledge Participants in Each Treatment

Table 7. Differences Between Experimental Treatment Groups

	1) **Observation only** (low prior domain knowledge) (n = 10)		2) **Observation + hands-on** (low prior domain knowledge) (n = 13)		3) **Observation only** (high prior domain knowledge) (n = 13)		t-test (1 vs. 2)	t-test (1 vs. 3)
	Mean	S.D.	Mean	S.D.	Mean	S.D.		
Total work experience	4.83	3.83	4.74	4.31	3.43	2.88	t(21) = 0.05, p = 0.96 (ns)	t(21) = 1.00, p = 0.33 (ns)
IS analysis experience	1.60	1.90	1.31	1.44	0.69	0.75	t(21) = 0.42, p = 0.68 (ns)	t(21) = 1.43, p = 0.18 (ns)
Prior SAP knowledge	0.67	0.99	0.54	0.75	1.23	1.40	t(21) = 0.36, p = 0.72 (ns)	t(21) = 1.08, p = 0.29 (ns)
Prior ERP knowledge	0.70	1.89	2.69	3.40	1.54	3.20	t(21) = 1.79, p = 0.09 (ns)	t(21) = 0.73, p = 0.47 (ns)
Age	26.25	4.35	29.81	5.76	28.62	5.13	t(21) = 1.62, p = 0.12 (ns)	t(21) = 1.17, p = 0.25 (ns)
Post treatment self-efficacy	7.83	0.53	6.90	1.50	7.21	1.49	t(21) = 1.85, p = 0.08 (ns)	t(21) = 1.24, p = 0.23 (ns)
Post treatment PEOU	7.4	2.14	7.60	1.82	8.19	0.93	t(21)= -0.24, p = 0.81 (ns)	t(21)= -1.20, p = 0.24 (ns)

Further, while Figure 2 suggests that participants with high prior domain knowledge benefited more from the observation approach than participants with low prior domain knowledge, we conducted an ANOVA test to assess this effect's significance. More specifically, in order to examine the significant influence that prior domain knowledge had on participants' knowledge structure accuracy in the observation-only approach (H2), we compared participants with high and low prior domain knowledge. As Table 8 shows, participants with high prior domain knowledge benefited significantly more from the observation-only approach than the low prior domain knowledge group ($F(1, 21) = 20.34$, $p = .000$), which supports H2. Figure 2, which shows that participants with high prior domain knowledge acquired more accurate knowledge structures in the observation-only treatment ($M = 0.46$, $SD = 0.16$) than those with low prior domain knowledge ($M = 0.15$, $SD = 0.18$), further provides support for H2. Again, as Table 7 shows (t-test 1 vs. 3), we found no significant differences in terms of work experience, systems analysis experience, SAP/ERP knowledge, and age between the high and low prior domain knowledge participants in the observation-only treatment, which suggests these factors did not likely affect the observed results.

Table 8. ANOVA Results for the Effect that Prior Domain Knowledge had on Participants' Knowledge Structure Accuracy (Observation Only, H3)

	Sum of squares	Df.	Mean square	F	Sig.
Between groups	.556	1	.556	20.342	**0.000**
Within groups	.574	21	.027		
Total	1.130	22			

Further, we examined the influence that participants' knowledge structure accuracy had on their declarative knowledge and conceptual model accuracies (H3 and H4, respectively) via a regression analysis. As Table 9 shows, we found that participants' knowledge structure accuracy significantly influenced their declarative knowledge accuracy scores and the accuracy of their conceptual model ($\beta = 0.368$, $t(41) = 2.531$, $p = 0.015$, and $\beta = 0.316$, $t(41) = 2.054$, $p = 0.047$), which supports both H3 and H4.

Table 9. Regression results: Influence that Participants' Knowledge Structure Accuracy had on the Accuracy of their Declarative Knowledge and Conceptual Model

	Declarative knowledge			Conceptual model		
Variable	B	SE (B)	β	B	SE (B)	β
Knowledge structure accuracy	3.919	1.548	.368*	7.755	3.776	.316*
R^2		.135			.100	
F		6.408*			4.218*	
* p < 0.05						

5 Discussion

In this study, we investigated and compared how effectively two theory-based learning approaches help IS analysts understand users' work processes. Hence, we compared the learning effectiveness of 1) observing a user perform a work process (observation only) and 2) first observing a user and then actually performing the work process (observation plus hands-on). We found that participants' domain-specific knowledge significantly moderated the influence that the two learning approaches had on their knowledge structure's accuracy. Further, we conducted a post hoc analysis and did not find a direct significant difference between the two learning approaches in terms of participants' knowledge structure accuracy ($F(1, 41) = 0.89$, $p = 0.35$), which the significant and large interaction effect that we observed (see Figure 2) between the learning approach and participants' domain knowledge (which they possessed before participating in the experiment) explains. More specifically, we found the accuracy of participants' knowledge structures to depend on their prior domain knowledge: participants who had low prior domain knowledge learned significantly more in the observation plus hands-on treatment than in the observation-only treatment. As Figure 2 shows, after going through the observation plus hands-on treatment, participants with low prior domain knowledge did not have significantly different knowledge structure scores than participants who already had high prior domain knowledge ($M = .39$ and $.38$, $SD = .19$ and $.29$, respectively; $t(18) = 0.14$, $p = .89$). These results concur with SCT and suggest that the observation plus hands-on approach to understanding users' work processes can be an effective learning approach for analysts who have low domain knowledge (domain novice analysts).

In contrast, participants who had prior domain knowledge did not benefit from the hands-on approach. This finding supports the previous cognitive learning literature by showing that experts' rich knowledge structures enabled them to more easily assimilate new knowledge into their existing knowledge structures by using observation, which rendered the hands-on approach redundant. Further, due to their richer and more organized knowledge structures, expert participants learned the work processes they observed significantly better than novices (i.e., they benefited from the observation-only approach significantly more than novice participants).

In addition, knowledge structure accuracy significantly influenced declarative knowledge and conceptual modeling task accuracy. These findings concur with past research that has found that individuals who possess high domain knowledge acquire and organize information more effectively than those who possess lower domain knowledge (Armstrong & Hardgrave, 2007; Schenk et al., 1998; Vitalari, 1985).

5.1 Study Limitations

Despite the general concerns regarding the external validity of experiments in a laboratory setting (even though we conducted an experimental task that accurately simulated actual tasks that actors in organizational contexts perform), the controlled environment enables researchers to rigorously control several potential confounding factors. Given that we lack prior research in this area, the experiment's strong internal validity provides an effective method for testing the influence of the two treatments.

We also note that our participants comprised university students who might not have had the same motivations as analysts working in organizational settings. In an effort to minimize this limitation, we carefully selected participants in order to ensure they represented actual IS analysts' educational profile and skills (e.g., they had an average of 4.26 years of work experience in the IS field, and 26 had more than a year of work experience as actual IS analysts). We also provided them with a performance-based reward as an incentive. Interestingly, all participants requested to see their results when the study ended, which suggests that they felt motivated to perform well in their experimental task. Nevertheless, the careful selection criteria resulted in a final sample with 43 participants; while we would have desired a larger sample size, the significant statistical support for H1 and H2 and the large effect sizes suggest that the sample size was adequate.

Another potential limitation concerns our using the modified activity-data matrix as a conceptual model rather than the DFD. Even though formal modeling approaches can fall "into disuse" in organizations due to their complexity (Wand & Weber, 2002, p. 364), one could view our using a non-standard matrix as a limitation. However, as it has also happened in many past studies (Neill & Laplante, 2003), pilot participants in our study could not develop DFDs (for a related discussion, see Wand & Weber, 2002), which meant we had to use an alternative tool. The activity-data matrix that we used has a similar objective to a DFD as it provides a physical artifact that maintains the DFD's functional perspective (Curtis et al., 1992) and depicts the data flows associated with major work process activities. Furthermore, given its simplicity, an activity-data matrix has the advantage of minimizing the potential confounding effects from participants' modeling skills and knowledge.

5.2 Implications for Research and Practice

Our findings have several important implications for research. First, we compared and found empirical support for two relatively well-established theory-based behavioral modeling methods in the IS training and learning literature. While the IS literature has long established that observation can provide a key way to acquire knowledge (e.g., Gupta & Bostrom, 2013; Yi & Davis, 2003), our findings suggest that, when analysts have limited knowledge about a domain for which they develop or implement an IS, adding a hands-on activity can provide a useful approach that can help them effectively learn the concepts that underlie work processes.

Further, past empirical research that has relied on social cognitive theory (SCT) has also largely focused on identifying the effectiveness of training methods for a homogenous group of domain-novice individuals (Gupta et al., 2010). As such, our findings contribute to the cognitive psychology literature by specifying and explaining the boundary conditions of the relatively well-established SCT. More specifically, our findings help explain the moderating effect that prior domain knowledge has on the effectiveness of different learning approaches and suggest that, while individuals with high prior domain knowledge tend to learn equally well with either approach, an observation plus hands-on approach can be more effective for novice learners than an observation-only approach. These findings have particular relevance for the IS training (Gupta et al., 2010; Santhanam et al., 2013) and requirements analysis (Byrd et al., 1992) literatures that address users' and analysts' knowledge acquisition. With few exceptions (i.e., Schenk et al., 1998; Vitalari, 1985), past research in those areas has largely neglected to consider learner characteristics. Our findings suggest that learners' prior knowledge constitutes an important characteristic since it likely influences the efficacy of the knowledge acquisition approach they will use.

Further, our findings also constitute an important contribution to cognitive research in systems analysis and design as they represent a first step in addressing two "enduring" questions in cognitive IS research: 1) how to improve analysts' declarative knowledge recall (Browne & Parsons, 2012) and 2) how to improve their mental models of users' work processes (Davern et al., 2012). With our study, we contribute to this work by measuring IS analysts' knowledge structures and observing that these structures' accuracy positively affects analysts' declarative knowledge (memory) and physical representation of work processes. While past IS training and learning research has used declarative knowledge and skill reproduction more than other learning measures (Gupta et al., 2010), our paper likely represents the first in the IS training and learning literature to measure participants' knowledge structures.

Our findings also have several practical implications. In general, IS project failures tend to significantly and negatively affect many organizations' profitability. The fact that many IS projects continue to still fail and/or face challenges due to inadequate system functionalities strongly suggests that we need to further empirically investigate different approaches than the ones that analysts currently use in order to help them better understand users' work processes. Hence, with this study, we contribute to organizational practice by addressing a real-world problem and suggest that analysts who have low knowledge (about the domain for which they develop a system) can develop accurate knowledge structures of users' work processes by first observing the users perform their work before executing the users' tasks themselves.

6 Conclusion

The idea that hands-on experience enhances observational learning has been central to theories about adult learning, such as experiential learning (Kolb, 1984), learning-by-doing (Argyris & Schön, 1978), and active learning (Bell & Kozlowski, 2008), which build on the philosophy of experiential education (Dewey 1938). Also, based on the influential SCT (Bandura, 1986), the idea that hands-on experience can enhance observation and promote individuals to develop knowledge structures has found much support (except for some mixed results). In this paper, we propose that hands-on learning may depend on analysts' prior domain knowledge. We conducted a study and found that, while novice learners benefited from the added hands-on approach, individuals with high prior domain knowledge did not. These findings underscore the importance of identifying and specifying the work process knowledge that analysts need to acquire and the need to investigate this knowledge under different contextual conditions.

Acknowledgments

We thank the senior editor and the anonymous reviewers for their valuable time and constructive comments that improved the paper. We also thank the Canada Research Chair in Information Technology Implementation and Management for funding.

References

Acton, W. H., Johnson, P. J., & Goldsmith, T. E. (1994). Structural knowledge assessment: Comparison of referent structures. *Journal of Educational Psychology*, *86*(2), 303-311.

Alter, S. (2001). Which Life Cycle—Work system, information system, or software? *Communications of the Association for Information Systems*, *7*, 1-52.

Anderson, J. (1982). Acquisition of cognitive skill. *Psychological Review*, *89*(4), 369-406.

Argyris, C., & Schön, D. A. (1978). *Organizational learning: A theory of action perspective*. Reading, MA: Addison-Wesley.

Armstrong, D. J., & Hardgrave, B. C. (2007). Understanding mindshift learning: The transition to object-oriented development. *MIS Quarterly*, *31*(3), 453-474.

Armstrong, D. J., Riemenschneider, C. K., & Giddens, L. G. (2018). The advancement and persistence of women in the information technology profession: An extension of Ahuja's gendered theory of IT career stages. *Information Systems Journal*, *28*(6), 1082-1124.

Ball, L. J., & Ormerod, T. C. (2000). Applying ethnography in the analysis and support of expertise in engineering design. *Design Studies*, *21*(4), 403-421.

Bandura, A. (1986). *Social foundations of thought and action: A social-cognitive View*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1999). Social cognitive theory: An agentic perspective. *Asian Journal of Social Psychology*, *2*(1), 21-41.

Bell, B. S., & Kozlowski, S. W. J. (2008). Active learning: Effects of core training design elements on self-regulatory processes, learning, and adaptability. *Journal of Applied Psychology*, *93*(2), 296-316.

Beyer, H. R., & Holtzblatt, K. (1995). Apprenticing with the customer. *Communications of the ACM*, *38*(5), 45-52.

Browne, G. J., & Parsons, J. (2012). More enduring questions in cognitive IS research. *Journal of the AIS*, *13*(12), 1000-1011.

Burton-Jones, A., Wand, Y., & Weber, R. (2009). Guidelines for empirical evaluations of conceptual modeling grammars. *Journal of the AIS*, *10*(6), 495-532.

Byrd, T. A., Cossick, K. L., & Zmud, R. W. (1992). A synthesis of research on requirements analysis and knowledge acquisition techniques. *MIS Quarterly*, *16*(1), 117-138.

Carroll, J. M., Mack, R. L., Lewis, C. H., Grischkowsky, N. L., & Robertson, S. (1985). Exploring exploring a word processor. *Human-Computer Interaction*, *1*, 283-307.

Chi, M. T. H., Glaser, R., & Rees, E. (1982). Expertise in problem solving. In R. J. Sternberg (Ed.), *Advances in the psychology of human iIntelligence*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Compeau, D., Marcolin, B., Kelley, H., & Higgins, C. (2012). Research commentary: Generalizability of information systems research using student subjects—a reflection on our practices and recommendations for future research. *Information Systems Research*, *23*(4), 1093-1109.

Curtis, B., Kellner, M. I., & Over, J. (1992). Process modeling. *Communications of the ACM*, *35*(9), 75-90.

Davern, M., Shaft, T., & Te'eni, D. (2012). Cognition matters: Enduring questions in cognitive IS research. *Journal of the Association for Information Systems*, *13*(4), 273-314.

Davis, F. D., & Yi, M. Y. (2004). Improving computer skill training: Behavior modeling, symbolic mental rehearsal, and the role of knowledge structures. *Journal of Applied Psychology*, *89*(3), 509-523.

Day, E. A., Arthur, W., & Gettman, D. (2001). Knowledge structures and the acquisition of a complex skill. *Journal of Applied Psychology*, *86*(5), 1022-1033.

De Jong, T., & Ferguson-Hessler, M. G. (1996). Types and qualities of knowledge. *Educational Psychologist*, *31*(2), 105-113.

Dennis, A., Wixom, B. H., & Tegarden, D. (2015). *Systems analysis and design: An object-oriented approach with UML*. New York, NY: John Wiley & Sons.

Dewey, J. (1938). *Experience and education*. New York, NY: Kappa Delta Pi.

Dorsey, D. W., Campbell, G. E., Foster, L. L., & Miles, D. E. (1999). Assessing knowledge structures: relations with experience and posttraining performance. *Human Performance*, *12*(1), 31-57.

Frese, M., Albrecht, K., Altmann, A., Lang, J., Papstein, P. V., Peyerl, R., & Wendel, R. (1988). The effects of an active development of the mental model in the training process: Experimental results in a word processing system. *Behaviour and Information Technology*, *7*(3), 295-304.

Gallivan, M. J., & Keil, M. (2003). The user-developer communication process: A critical case study. *Information Systems Journal*, *13*(1), 37-68.

Glaser, R. (1990). The reemergence of learning theory within instructional research. *American Psychologist*, *45*(1), 29-39.

Goldsmith, T., Johnson, P., & Acton, W. (1991). Assessing structural knowledge. *Journal of Educational Psychology*, *83*(1), 88-96.

Gordon, M. E., Slade, L. A., & Schmitt, N. (1986). The “science of the sophomore” revisited: From conjecture to empiricism. *Academy of Management Review*, *11*(1), 191-207.

Gupta, S., & Bostrom, R. P. (2013). An investigation of the appropriation of technology-mediated training methods incorporating enactive and collaborative learning. *Information Systems Research*, *24*(2), 454-469.

Gupta, S., Bostrom, R. P., & Huber, M. (2010). End-user training methods: What we know, need to know. *SIGMIS Database*, *41*(4), 9-39.

Harris, N., Cushman, P., Kruck, S. E., & Anderson, R. D. (2009). Technology majors: Why are women absent? *Journal of Computer Information Systems*, *50*(2), 23-30.

Huang, I.-L., & Burns, J. R. (2000). A cognitive comparison of modeling behaviors between novice and expert informationanalysts. In *Proceedings of the Americas Conference on Information Systems.*

Iivari, J., Hirschheim, R., & Klein, H. K. (2004). Towards a distinctive body of knowledge for information systems experts: Coding ISD process knowledge in two IS journals. *Information Systems Journal*, *14*(4), 313-342.

Johnson, R. D., & Marakas, G. M. (2000). Research report: The role of behavioral modeling in computer skills acquisition—Toward refinement of the model. *Information Systems Research*, *11*(4), 403-417.

Jonassen, D. H., Beissner, K., & Yacci, M. (1993). *Structural knowledge: Techniques for representing, conveying, and acquiring structural knowledge*. New York, NY: Routledge.

Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instruction. *Educational Psychology Review*, *19*(4), 509-539.

Keith, N., & Frese, M. (2008). Effectiveness of error management training: A meta-analysis. *Journal of Applied Psychology*, *93*(1), 59-69.

Khatri, V., & Vessey, I. (2016). Understanding the role of IS and application domain knowledge on conceptual schema problem solving: A verbal protocol study. *Journal of the Association for Information Systems*, *17*(12), 759-803.

Khatri, V., Vessey, I., Ramesh, V., Clay, P., & Park, S.-J. (2006). Understanding conceptual schemas: Exploring the role of application and domain knowledge. *Information Systems Research*, *17*(1), 81-99.

Ko, D.-G., Kirsch, L. J., & King, W. R. (2005). Antecedents of knowledge transfer from consultants to clients in enterprise system implementations. *MIS Quarterly*, *29*(1), 59-85.

Kolb, D. A. (1984). *Experiential learning: Experience as the source of learning and development*. Englewood Cliffs, NJ: Prentice-Hall.

Kozlowski, S. W. J., Gully, S. M., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. (2001). Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational Behavior and Human Decision Processes*, *85*(1), 1-31.

Kraiger, K., Ford, J. K., & Salas, E. (1993). Application of cognitive, skill-based, and affective theories of learning outcomes to new methods of training evaluation. *Journal of Applied Psychology Monograph*, *78*(2), 311-328.

Krajewski, L. J., Ritzman, L. P., & Malhotra, M. K. (2006). *Operations management. Processes and value chains.* Boston, MA: Addison-Wesley.

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*, *77*(6), 1121-1134.

Kruskal, J. B. (1964). Nonmetric multidimensional method: A numerical method. *Psychometrica*, *29*, 115-129.

Léger, P., Feldstein, H. D., Babin, G., Charland, P., Robert, J., & Lyle, D. (2011). Business simulation training in information technology education: Guidelines for new approaches in IT training. *Journal of Information Technology Education*, *10*, 39-53.

Léger, P. M. (2006). Using a simulation game approach to teach enterprise resource planning concepts. *Journal of Information Systems Education*, *17*(4), 441-447.

Luo, W., & Tung, Y. A. (1999). A framework for selecting business process modeling methods. *Industrial Management and Data Systems*, *99*(7), 312-319.

Mackay, J. M., & Elam, J. J. (1992). A comparative study of how experts and novices use a decision aid to solve problems in complex knowledge domains. *Information Systems Research*, *3*(2), 150-172.

Marakas, G. M., & Elam, J. J. (1998). Semantic structuring in analyst acquisition and representation of facts in requirements analysis. *Information Systems Research*, *9*(1), 37-63.

Markus, M. L., & Mao, J.-Y. (2004). Participation in development and implementation—updating an old, tired concept for today's IS contexts. *Journal of the Association for Information Systems*, *5*(11/12), 514-544.

Mathiassen, L., Saarinen, T., Tuunanen, T., & Rossi, M. (2007). A contingency model for requirements development. *Journal of the Association for Information Systems*, *8*(11), 569-597.

Méndez Fernández, D., Wagner, S., Kalinowski, M., Felderer, M., Mafra, P., Petro, A., & Wieringa, R. (2017). Naming the pain in requirements engineering: contemporary problems. *Causes, and Effects in Practice, Empirical Software Engineering*, *22*(5), 2298-2338.

Millen, D. R. (2000). Rapid ethnography: Time deepening strategies for HCI field research. In Proceedings of *the 3rd Conference on Designing Interactive Systems: Processes, Practices, Methods, and Techniques*.

Nambisan, S., Agarwal, R., & Tanniru, M. (1999). Organizational mechanisms for enhancing user innovation in information technology. *MIS Quarterly*, *23*(3), 365-395.

Neill, C. J., & Laplante, P. A. (2003). Requirements engineering: The state of the practice. *IEEE Software*, *20*(6), 40-45.

Ortiz de Guinea, A., & Webster, J. (2011). Are we talking about the task or the computer? An examination of the associated domains of task-specific and computer self-efficacies. *Computers in Human Behavior*, *27*(2), 978-987.

Robertson, I. T. (1990). Behaviour modelling: Its record and potential in training and development. *British Journal of Management*, *1*(2), 117-125.

Rowe, A. L., Hall, E. P., Cooke, N. J., & Halgren, T. L. (1996). Toward an on-line knowledge assessment methodology: Building on the relationship between knowing and doing. *Journal of Experimental Psychology: Applied*, *2*(1), 31-47.

Santhanam, R., Seligman, L., & Kang, D. (2007). Postimplementation knowledge transfers to users and information technology professionals. *Journal of Management Information Systems*, *24*(1), 171-199.

Santhanam, R., Yi, M. Y., Sasidharan, S., & Park, S. H. (2013). Toward an integrative understanding of information technology training research across information systems and human-computer interaction: A comprehensive review. *AIS Transactions on Human-Computer Interaction*, *5*(5), 134-156.

Satzinger, J. W., Jackson, R. B., & Burd, S. D. (2016). *Systems analysis and design in a changing world.* Boston, MA: Cengage Learning.

Schenk, K. D., Vitalari, N. P., & Davis, K. S. (1998). Differences between novice and expert systems analysts: What do we know and what do we do? *Journal of MIS*, *15*(1), 9-50.

Shuraida, S., & Barki, H. (2013). The influence of analyst communication in IS projects. *Journal of the Association for Information Systems*, *14*(9), 482-520.

Standish Group. (2015). *CHAOS Report 2015*. Retrieved from https://www.infoq.com/articles/standish-chaos-201.

Sweller, J. (1988). Cognitive load during problem solving. *Cognitive Science*, *12*, 257-285.

Tannenbaum, S. I., & Yukl, G. (1992). Training and development in work organizations. *Annual Review of Psychology*, *43*(1), 399-441.

Taylor, P. J., Russ-Eft, D. F., & Chan, D. W. L. (2005). A meta-analytic review of behavior modeling training. *Journal of Applied Psychology*, *90*(4), 692-709.

U.S. Department of Labor. (2013). *Computer systems analysts.* Retrieved from http://www.bls.gov/ooh/computer-and-information-technology/computer-systems-analysts.htm

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342-365.

Vitalari, N. P. (1985). Knowledge as a basis for expertise in systems analysis: An empirical study. *MIS Quarterly*, *9*(3), 221.

Wand, Y., & Weber, R. (2002). Research commentary: Information systems and conceptual modeling—a research agenda. *Information Systems Research*, *13*(4), 363-376.

Wilkinson, L. (1986). *SYSTAT, the system for statistics*. Evanston, Il: SYSTAT.

Yi, M. Y., & Davis, F. D. (2001). Improving computer training effectiveness for decision technologies: Behavior modeling and retention enhancement. *Decision Sciences*, *32*(3), 521-544.

Yi, M. Y., & Davis, F. D. (2003). Developing and validating an observational learning model of computer software training and skill acquisition. *Information Systems Research*, *14*(2), 146-169.

Appendix A: ERPsim[7]

ERPsim is business simulation software that simulates near-real-life business contexts that feature large corporate information systems. It comes with an SAP software interface that enables the simulation participants to retrieve information about an organization's ongoing operations and make decisions accordingly in an environment that resembles a real-world operational business context.

ERPsim provides three functions. First, it simulates a buyer market for an organization's products. Second, it automates some administrative business functions such as invoicing, shipping, and goods receipt in order to allow the business simulation participants to focus on operational and strategic decision making. Third, it simulates time passing by compressing virtual simulated days into minutes. In the present study, we compressed each virtual day into two minutes.

Also note that more than a hundred universities and more than a dozen Fortune 1000 organizations have used ERPsim in order to develop SAP skills mainly due to its contextual realism (Léger et al., 2011).

[7] The SAP University Alliance Competency Centers and the SAP University Alliance has free licenses to use ERPsim in the academic world.

Appendix B: Example Items for Assessing Domain Knowledge Accuracy

Please check the box that best completes the statement or answers the question*

13) A forecast is typically more accurate for
- ☐ Groups of items rather than for individual items
- ☐ Daily rather than monthly periods of time
- ☐ Physical units rather than monetary units
- ☐ Far out in the future rather than nearer time periods

14) Which of the following is used to convert the master production schedule into detail requirements?
- ☐ Production planning
- ☐ Rough-cut capacity planning
- ☐ Production activity control
- ☐ Material requirements planning

15) The main objective of the materials requirement planning (MRP) process is to:
- ☐ Identify the product components
- ☐ Classify the materials into product groups
- ☐ Determine the required amount of products
- ☐ Determine the material stocking location

16) Independent demand is
- ☐ Demand not related to the demand for any other product or service
- ☐ Demand that is derived from that of a second item
- ☐ Demand that is increasing in a linear trend from year to year
- ☐ Demand that demonstrates a cyclical wavelike pattern

The following steps describe the process that we followed to develop the pre-treatment domain knowledge questions:

1) To capture the operation and logistics task domain knowledge, we used a deductive approach based on the simulation task activities.
2) We selected multiple choice questions related to those concepts from test banks that accompany a widely used operations management textbook and a professional publication: we selected seven questions from Krajewski, Ritzman, and Malhotra (2006) and two questions from the APICS CPIM 2002 certification exam for supply chain professionals.
3) We pre-tested these questions with two PhD students who were familiar with the experimental task. We asked them if they found the pre-treatment questions reasonable measures of knowledge about the concepts that pertain to the simulated task. Further, we interviewed the 17 pilot test participants after the experiment in order to elicit their thoughts about the pre-treatment and declarative knowledge questions in addition to the treatment conditions. Based on their feedback, we eliminated four questions for lack of relevance or redundancy.

To examine the extent to which the pre-treatment questions assessed domain knowledge, we compared the MBA and computer science (CS) students' pre-treatment domain knowledge. We expected that, as they take operations management courses, MBA students would be likely to have more domain knowledge than CS students. Indeed, MBA students' pre-treatment domain knowledge was significantly higher than CS students' pre-treatment domain knowledge ($F(1, 30) = 5.54$, $p = 0.025$).

Appendix C: Example Items for Assessing Declarative Knowledge

Accuracy Items

Please check the box with the most appropriate response:

75) Which of the following represent activities the business expert undertakes to manage the operations of the bottle distribution company?

- ☐ Invoicing customers
- ☐ Pricing products
- ☐ Paying suppliers
- ☐ Launching purchase orders to replenish products

(Answer: pricing products and launching purchase orders to replenish products)

76) The business expert performs the following steps to replenish product inventory:

- ☐ Perform the MRP run
- ☐ Pay suppliers for ordered products
- ☐ Launch purchase orders
- ☐ Process invoice received from supplier

(Answer: perform the MRP run and launch purchase orders)

77) The 1L Spritz is selling better than expected and, at the current rate, will be out of stock in one day. Which of the following actions will likely decrease the sales rate of this product and increase its profit margin per unit sold?

- ☐ Increase the product's price
- ☐ Decrease the product's sales forecast
- ☐ Order more inventory
- ☐ Decrease the product's marketing expenditure

(Answer: increase the product's price)

78) Which of the following reports **does not** update on a daily basis?

- ☐ Purchase order tracking report
- ☐ Inventory report
- ☐ Price market report
- ☐ Summary sales report

(Answer: summary sales report)

Please check true or false for each statement below:

85) The company repackages the products it sells (false)
86) The purchase order quantity partly depends on the forecast (true)
87) The company does not keep inventory of the products it sells (false)

Appendix D: Assessing Participants' Knowledge Structures

Domain-specific knowledge structure refers to how an individual organizations the “interrelationships between the important concepts in that domain” (Goldsmith et al., 1991, p. 88). In order to measure individuals' knowledge structures, cognitive learning researchers have used a structural measurement approach in which learners estimate the pairwise similarity or proximity of important domain concepts that the researchers then submit to a scaling or clustering algorithm (Rowe et al. 1996). Consequently, the researchers score and assess the resulting individual map according to its similarity to a prototype or expert map (Goldsmith et al., 1991).

Based on previous studies (Goldsmith et al., 1991; Rowe et al., 1996; Dorsey et al., 1999; Day et al., 2001), we describe the structural measurement approach we used to assess participants' knowledge structure below.

Knowledge Elicitation

In order to elicit how well participants understood relationships between task concepts, we needed to identify the first the key concepts that represented the task domain. While no empirically validated procedures for selecting concepts in cognitive structure research exists, past literature suggests that the selected concepts need to be 1) relevant, 2) specific to the training context, and 3) widely representative of the elicited knowledge domain (Dorsey et al., 1999). As such, the first author and an external researcher (both knowledgeable in the ERPsim task) constructed the concepts by considering the task-related procedures and decisions. As a result, they created 13 task-central concepts that they sent to a panel with three researchers who had designed the simulation software to review. Based on their suggestions, we deemed one concept redundant and deleted it, and we made minor semantic revisions to others, which resulted in the following 12 concepts: product cost, distribution channel, marketing expenditure, material requirements planning, product forecast quantity, product inventory level, product market price, product supplier, purchase orders, sales orders, regional markets, and replenishment lead time. Pairing these 12 concepts resulted in 66 concept pairs (n(n-1)/2)

Following the training, we asked the respondents to assess the relatedness between each concept pair using 10-point scales (1 = completely unrelated to 10 = highly related). Consistent with past research (Goldsmith et al., 1991), we asked respondents to base their answers on their intuitive first judgments as in the following example.

Table D1. Structural Assessment Questions

Instructions for questions 9 to 74:
Please rate the relatedness of the terms below. Terms can be related in many ways – they can be in the same category, used in a similar way, or even related by time. We would say that “bird” and “nest” were highly related as well as “hurt” and “ambulance”, “early” and “morning”, and so forth.

For each pair of terms listed below, circle a number from 1 to 10 to indicate how related you think the terms are. Smaller numbers mean less related and larger numbers mean more related. Use what you have learned about the operations of the wholesale distribution company to make your ratings. Try not to spend more than 10 seconds to decide how related a pair is. We are interested in your first impressions.

	Completely unrelated							**Highly related**		
9: regional markets—product cost	1	2	3	4	5	6	7	8	9	10
10: product inventory level—distribution channel	1	2	3	4	5	6	7	8	9	10
11: replenishment lead time—distribution channel	1	2	3	4	5	6	7	8	9	10
12: regional markets—marketing expenditure	1	2	3	4	5	6	7	8	9	10

Similarly, we also requested the study's three expert panel members (ERPsim developers) to complete the structural assessment measure that we show above in order to create the referent structure.

Knowledge Representation

Based on the idea that "experts' organization and comprehension of domain knowledge are a close approximation of the true representation of that domain" (Day et al., 2001, p. 1023) and prior empirical research that has demonstrated the superiority of averaged expert-referent structures (Acton, Johnson, & Goldsmith, 1994), we averaged the expert panel's structural assessments (pairwise relations) to provide the referent domain representation. Note that the three experts' responses significantly converged with correlation values of $r_{12} = 0.65$, $r_{13} = 0.76$, and $r_{23} = 0.75$, $p < 0.01$.

While this raw proximity data represents' the domain-specific knowledge, it contains noise (Goldsmith et al., 1991); thus, we used multi-dimensional scaling (MDS) to represent the data's underlying organization (Kruskal, 1964; Wilkinson, 1986). More specifically, we used proximity scaling (PROXSCAL) in SPSS to represent the structure of the experts' referent structure based on their averaged pairwise proximity matrix. The resulting map portrays how the experts assessed similarity/dissimilarity between the domain concepts along a given number of dimensions. Objects closer on the map show that individuals perceive them as more similar, while objects further apart as more dissimilar. As Appendix F shows, a two-dimensional scale provided an acceptable fit that positioned data points in the space in a manner consistent with the positions of all other data points. This two dimensional map provides a Euclidian distance between each concept pair and serves as the referent map for evaluating the experimental participants' knowledge.

Knowledge Evaluation

Subsequently, we mapped each participants' proximity matrix using PROXSCAL in SPSS, which also provided a Euclidian distance matrix between all concept pairs in the two-dimensional space. We then correlated this pairwise Euclidian distance with the experts' MDS spatial representation (i.e., pairwise Euclidian distance). A higher correlation coefficient between the participant's spatial representation and the referent spatial representation suggests a more organized knowledge structure. The participants' correlation coefficients with the referent structure ranged from -0.11 to 0.69 with an average of 0.35.

Appendix E: Systems Design Task: Modified Activity-Data Matrix

Table E1. Modified Activity-data Matrix

Instructions for questions 88 to 92:
Using the table of activities and data flows provided below:

1) Identify and write the five activities the expert user performed in the video to manage the company's operations. Choose the relevant activities from the activity list.
2) Identify and write the information necessary (data inputs) to perform each activity. Choose the data input(s) from the data flow list.
3) Identify and write the information resulting (data outputs) from each activity. Choose the data output(s) from the data flow list.

Note 1: the list provided below contains irrelevant activity items and data flow items. Choose only the relevant items according to the tasks the expert user explained and performed.
Note 2: a data flow can be a data input for more than one activity.

Activity	Data input(s)	Data output(s)
88: Activity 1:		
:		
92: Activity 5:		

Table E2. Sample of Activities

Accept customer orders
Change purchase order quantity
Manage product pricing

Table E3. Sample of Data Flows

Purchase orders
Product dimensions
Average market product price
Independent demand (forecast)

Appendix F: Multidimensional Scaling Elbow Criterion (Scree Plot) and Goodness of Fit Tests

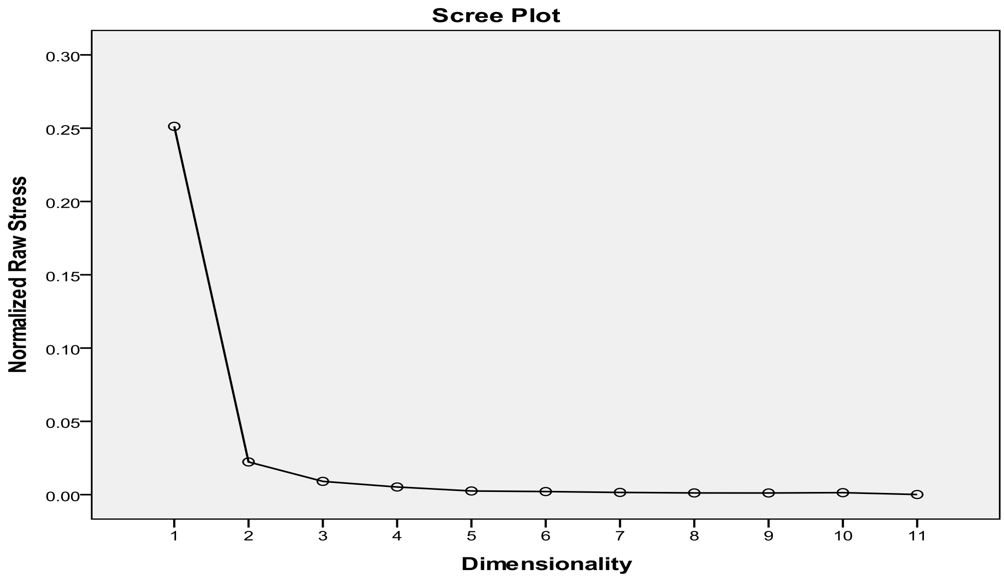

Figure F1. Goodness of Fit based on Two Dimensions

Table E1. Goodness of Fit Tests

Normalized raw stress	**.0221**
Stress-I	.1488[a]
Stress-II	.3807[a]
S-Stress	.0588[b]
Dispersion accounted for (D.A.F.)	.9779
Tucker's coefficient of congruence	.9889

Normalized raw stress represents the degree to which the algorithm could position data points in the space in a manner consistent with the positions of all other data points. The lower the coefficient, the greater the consistency. In general, researchers consider a 0.15 or smaller stress coefficient acceptable.

About the Authors

Shadi Shuraida is an Assistant Professor of Information Technologies at TÉLUQ—University of Quebec. He completed his PhD in Information Technologies from HEC Montreal, and his main research interests focus on the development, implementation, and impact of information systems. His research has been published or is forthcoming in the *European Journal of Information Systems, Journal of the Association for Information Systems, International Journal of Production Economics*, and *AIS Transactions on Human-Computer Interaction*.

Henri Barki retired from HEC Montréal in 2017 and was honored as a Professor Emeritus of Information Technologies. He also is a member of the Royal Society of Canada since 2003 and has served on the editorial boards of *MIS Quarterly*, *Data Base for Advances in Information Systems*, *Canadian Journal of Administrative Sciences*, *Gestion*, and *Management International.* His research efforts focused on the development, introduction and use of information technologies in organizations. Journals where his research findings were published include *Canadian Journal of Administrative Sciences, Data Base for Advances in Information Systems, Foundations and Trends in Information Systems, IEEE Transactions on Professional Communication, Information Systems Journal, Information Systems Research, Information & Management, INFOR, International Journal of Conflict Management, International Journal of e-Collaboration, International Journal of e-Government Research, Journal of the Association for Information Systems, Journal of Information Technology, Journal of MIS, Management Science*, *MIS Quarterly, Organization Science,* and *Small Group Research.*

Transactions on Human – Computer Interaction