CAN KNOWLEDGE BASED SYSTEMS BE DESIGNED TO

COUNTERACT DESKILLING EFFECTS?

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Abstract

The major public accounting firms are increasingly implementing restrictive audit support systems, which theoretically lead to de-skilling of novice accounting professionals. Research provides some evidence that such affects are present from the use of these systems. Our research focuses on redesigning knowledge-based systems in order to facilitate knowledge acquisition by system users in an effort to counteract potential de-skilling effects from use of such systems. Specifically, our research manipulates the design of the system interface to provide information cues in a screen format consistent with expert knowledge representations and manipulates the automatic provision versus voluntary use of explanations for users during the task completion stage in order to better understand how the decision is framed and how information is aggregated for expert like judgment processes. The results show that after using the knowledge-based system to complete a series of reenacted client engagements over a three-day training period, both the interface design manipulation and the automatic provision of explanations had a significant positive effect on novice accounting professionals development of expert like knowledge structures. The results of the study have important implications for the development of knowledge-based systems intended to support accounting professionals' (and other knowledge workers') expertise development processes.

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Research indicates that the major public accounting firms have increasingly implemented restrictive audit support systems designed to formalize and enforce the firm's audit methodology (Dowling and Leech 2007, 2014), improve audit efficiency and effectiveness (Banker et al. 2002; Bedard et al. 2008; Dowling 2009), increase competitive advantage (Carson and Dowling 2012), and enhance consistency of documentation in defense of regulatory pressures[1] (DeFond and Lennox 2011; Dowling and Leech 2014). These audit support systems become a form of management control system enforcing the firm's methodology and inducing consistency in audit procedures across engagements, but in order to be an effective control system these audit support systems must also actively restrict auditors' independent behavior (Dowling and Leech 2014).

Amidst these efforts to steadily increase automation of the audit process and structure the guidance provided during audit execution, little attention has been given to the potential for technology dominance effects and associated deskilling of auditors (Arnold and Sutton 1998; Dowling and Leech 2014). Deskilling can occur either from a professional losing knowledge they possessed as it atrophies from lack of use, or from new professionals not developing knowledge that professionals traditionally acquired because they have not had to develop the skill themselves due to technology support (Arnold and Sutton 1998). These effects could have significant ramifications by limiting development of auditor expertise, as auditors increasingly are dependent on such audit support systems (Arnold and Sutton 1998; Dowling and Leech 2007, 2014). Initial evidence on the effects of restrictive audit support systems on the development of staff auditors' knowledge indicates that such deskilling is occurring and is exacerbated when

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[1] The PCAOB has evaluated the audit processes embedded in all of the major accounting firms audit support systems.

systems are more structured and provide more extensive guidance (Dowling et al. 2008; Stuart and Prawitt 2012). Studying experienced auditors from multiple firms, Dowling et al. (2008) found that auditors from firms using more restrictive audit support systems performed worse on a business risk identification task when the system was not available than auditors from firms with less restrictive systems. In a very similar study looking specifically at two audit firms (one highly formalized and one less formalized), auditors from both firms performed equally well on the two simple tasks, while the auditors from the firm with more formalized audit processes allowing for less independent judgment performed significantly worse on the two complex tasks (Stuart and Prawitt 2012). These findings raise the research question, "Can systems be designed to both enhances performance and mitigate risk of deskilling?"

The purpose of this study is to explore the potential for specific system design enhancements to promote the development of expert-like knowledge structures in novice accounting professionals that will enhance expertise development when using knowledge-based systems. Two specific design interventions are of interest. First, research has shown that in less complex decision environments, developing system interfaces that organize screens to represent the patterns in expert cognitive structures facilitates the transfer of these knowledge structures to users (Rose et al. 2012). We extend this research to consider the viability of these interface organizations when the decision environment is complex and there are vastly more information cues that must be considered. Second, researchers have theorized that providing system explanations along with guidance to the user may facilitate knowledge transfer from a knowledge-based system to the user when the cognitive effort required can be minimized (Gregor and Benbasat 1999). However, high quality explanations can be complex to implement because explanations that are not geared to the current knowledge level of the users can be

dysfunctional (Arnold et al. 2006). To date, little research has examined knowledge-based systems that address these concerns. We study the potential to enhance the value of explanations by developing a novel system that systematically alters the knowledge level of explanations provided as accounting professionals gain experience.

This study examines the potential benefits of the two system design interventions on accounting professionals' development of cognitive knowledge structures similar to experts. The experimental process was embedded within training sessions for accounting firm staff. The training process revolved around three-day training sessions adopting constructivist learning strategies that prescribe immersion of the trainee in real case scenarios simulated through technology delivery to replicate actual engagement experiences in a condensed time frame (Crowe et al. 1996; Hannafin and Land 2000; Hirumi 2002; and Jonassen et al. 2008). A series of actual engagements were modeled through computer simulations that provided access to such things as actual client documentation and reenacted client interviews to enhance realism and provide the engagement experience in a condensed time period. The complexity of the cases steadily increased over the three-day training session. Six client engagements were reenacted and executed during the training—all being completed by each individual with the assistance of a knowledge-based system to assist in decision-making. Participants used one of four different knowledge-based system implementations that were derived from a 2 x 2 experimental design where we manipulated the interface design (generic versus expert knowledge structure interface) and the provision of explanations (automatically provided or provided through participant voluntary access) during system use.

Data were collected from 67 novice accounting professionals completing a three-day training session. The results indicate that the use of experts' cognitive knowledge structures to

organize the system interface and the use of automatic explanation provision both enhanced expertise development in a highly complex decision domain. We find that the potential deskilling of auditors can be mitigated, at least in part, by systems that visually represent the knowledge of experts or reduce the cognitive demands of a system by automating explanation provision and thereby assisting in the transfer of expertise to users.

The results of the research are important to both theory and practice. First, the results indicate that the use of experts' cognitive knowledge structures to drive interface design for systems supporting complex decisions can improve users' acquisition of expert-like knowledge structures. Second, by providing automatic explanations that match the user's level of knowledge acquisition, users are able to develop cognitive knowledge structures that more closely resemble those of experts despite work activities being focused on performance-oriented activities. This latter effect is significant in that prior research on explanations (e.g. Eining and Dorr 1991; Mascha 2001; McCall et al. 2008; Smedley and Sutton 2004; 2007; Steinbart and Accola 1994) has focused on development of fact-based and rule-oriented knowledge, but not on the cognitive knowledge structures that are necessary for the development of expertise (e.g. Choo and Curtis 2000; Davis and Yi 2004; Day et al. 2001; Goldsmith and Davenport 1990; Kraiger et al. 1993; Rose et al. 2007; Schvaneveldt 1990). Third, the results suggest that it is possible to counteract some of the deskilling effects from using highly structured knowledge-based systems through system design interventions.

The remainder of this paper is organized in four sections. Section two overviews prior research, setting the background for the research and leading into the theory and hypotheses development. The third section overviews the methodology while the fourth section summarizes the results. The last section discusses implications for future research.

BACKGROUND, THEORY AND HYPOTHESES

Decision aids such as audit support systems are an integral part of the work environment of professional accountants (see Dowling and Leech 2007). Such decision aids are also an integral part of accounting professionals' learning experience and opportunities for knowledge development (Libby 1995; Dowling et al. 2008; Rose 2002; 2005; Rose and Wolfe 2000). However, the focus of such systems is largely on work performance and ensuring the efficiency and effectiveness of the work process along with the documentation needed to meet statutory and regulatory requirements (Banker et al. 2002; Bedard et al. 2008; DeFond and Lennox 2011; Dowling and Leech 2014). Little consideration has been given to how such systems can better support the learning experience of novice professionals.

The lack of concern for the learning experience provided by such systems has both short and long-term ramifications that are potentially significant. While novice professionals will presumably make better decisions when using these systems (Bedard et al. 2008; DeFond and Lennox 2011), research is mixed. Some research shows improvement in decision making when novices use such systems (e.g. McCall et al. 2008), while other research demonstrates the potential for such systems to have negative effects on decision making and potentially accentuate decision biases (Arnold et al. 2004b; Masselli et al. 2002; Seow 2011).

Longer term, there are theoretical reasons to believe that such systems can lead to deskilling as users become dependent on the systems to perform tasks and do not develop the ability to perform the task themselves, nor to recognize when the system is not working effectively (Arnold and Sutton 1998). Preliminary evidence suggests these concerns are valid (McCall et al. 2008). Novices who used a knowledge management system to complete a learning task performed better than their manual counterparts when using the system; but, when the system was taken away, those learning with the knowledge management system performed

significantly worse. Perhaps even more concerning are the results from Dowling et al. (2008) that show that auditors averaging about six years of experience from firms that used restrictive audit support systems that provide strong decisional guidance performed much worse on a client business risk task than did similar auditors from firms using less restrictive systems with voluntary use requirements. There was a pattern of deskilling in the auditors from the firms with more restrictive audit support systems—the type of systems that are increasingly preferred by both novice users (Malaescu and Sutton 2015) and the major international accounting firms deploying the systems (Dowling and Leech 2007; 2014).

The above leads to the basic research question, "Can these systems be designed in a way that both enhances performance and mitigates the risk of deskilling the user?" Two potential system design interventions are considered in this study. First, Rose et al. (2012) theorize that the development of a systems interface based on a visual layout consistent with expert knowledge structures can promote the development of similar knowledge structures by novice users. In a small scale prototype system, they find evidence supporting the potential effectiveness of such a strategy. Second, researchers for some time have explored the possibility of using explanation facilities embedded in systems to facilitate knowledge transfer to users (see Smedley and Sutton (2007) for a review of related accounting studies). Gregor and Benbasat (1999) provide a synthesis of the explanation facilities literature from both a design science and behavioral science view to identify how explanation facilities can be designed and implemented to provide the most benefit to systems users. They theorize that an effective explanation facility provides explanations tailored to the specific user through automatic provision during task completion.

Expert Knowledge Structures

The development of expert knowledge structures occurs in stages with the lower forms of

knowledge serving as a foundation for higher forms of knowledge (Anderson 1990, 2000; Kraiger et al. 1993). As shown in Figure 1, declarative knowledge develops as an individual explores the definitions, rules, and examples associated with a decision domain and procedural knowledge uses declarative knowledge to solve problems, make decisions, assess decision outcomes, and refine decision processes (Anderson 2000; McCall et al. 2008). As declarative and procedural knowledge work together, individuals begin to create a structure, which can be used in different situations (Fenwick 2000). In more advanced stages, individuals become experts in a domain as their knowledge structures become more expert-like (Cooke and Schvanelveldt 1988; Davis et al. 2003).

[Insert Figure 1 about here]

Prior research suggests that experts differ from novices in the amount, content, and organization of their domain knowledge (Sweller 1988; Glaser and Chi 1988; Chi et al. 1982). Compared to a novice, experts can perceive large meaningful patterns in their domain, have superior short- and long-term memory for domain-relevant information, represent problems at a deeper level, and spend more time analyzing a problem prior to attempting a solution to the problem. Further, knowledge organization is crucial for expert performance (Davis et al. 2003; Sweller 1993), is highly correlated with future decision performance (Kraiger and Cannon-Bowers 1995), and can fully mediate the relationship between training method and future decision performance (Davis and Yi 2004; Rose et al. 2007, 2012).

The challenge in accounting research has been one of identifying who really is an expert (Bonner and Lewis 1990). While experience leads to the opportunity for a professional to acquire knowledge and develop expertise, experience is a necessary but insufficient condition for expertise development (Bonner and Lewis 1990; Bonner et al. 1997; Libby 1995; Libby and Luft

1993). Learning from experience is hampered by not having a cognitive lens that is appropriate for cataloging experiences and the declarative and procedural knowledge to which the decision maker is exposed (Bonner et al. 1997). Getting the right categorization frame is imperative to the formation of a knowledge structure that facilitates expert decision making (Kopp & O'Donnell 2005; O'Donnell 2003; Schultz et al. 2010). For more complex decision processes, a holistic template can aid the decision makers' performance and facilitate the handling of the associated large number of information cues (Brewster 2011). Technology-based systems are one way of providing the necessary frame (O'Donnell and Schultz 2003).

Several methods are available to elicit knowledge representations, including word associations, card sorting exercises, multidimensional scaling, recall and chunking of concepts, and Pathfinder Network Analysis (Cooke 1999; Cooke and Schvanelveldt 1988; Davis et al. 2003). These methods have several steps in common, which are necessary to determine an individual's representation and organization of a domain of knowledge: (1) definition of the concept domain/ referent structure, (2) collection of the relatedness judgments from experts and novices, (3) use of the relatedness data to define a representation of the knowledge, and (4) interpretation and evaluation of the representation (Cooke 1994; Kraiger et al. 1993). The output from these knowledge mapping techniques can be used to determine a person's knowledge structure and to create a two dimensional representation or knowledge map of that structure (Goldsmith et al. 1991; Taricani and Clariana 2006).

Effective knowledge transfer from knowledge-based systems will result in knowledge structures in novices that resemble experts' knowledge structures, cognitive structures which change as a person becomes more of an expert in the subject (Goldsmith et al. 1991). Studies have investigated the differences in knowledge maps between experts and novices (Cooke and

Schvaneveldt 1988; Gillan et al. 1992; McKeithen et al. 1981). Results indicate that experts use fewer information cues and have more organized knowledge structures than novices. In a study of the knowledge structures of human computer interface design experts, experts cleanly separated networks and sub-networks while novices had much less differentiation, more links, and a higher number of weak links (Gillan et al. 1992). The results of recent studies suggest that using the knowledge structure of experts to develop knowledge transfer interventions will increase the efficacy of the intervention (e.g., Bielaczyc et al. 1995; Kraiger and Cannon-Bowers 1995; Sanchez 2004; Rose et al. 2007). This leads to the following hypothesis:

H_1:   Professionals using a knowledge-based system with an interface resembling the knowledge structure of an expert will develop a knowledge structure that is closer to that of an expert than will users of systems without such interfaces.

Explanation Facilities

Since the earliest development of knowledge-based systems for facilitating decision making, explanation facilities have been perceived as an important and valued feature. However, the development and delivery of these explanation facilities have rarely been theory driven, but rather an artifact of the designer's intuition. Frequently they come in the form of help menus that must be searched and often drilled down through multiple hyperlinks (Gregor and Benbasat 1999). Gregor and Benbasat (1999) put forth a theoretical basis for understanding how explanation facilities should be constructed, made available, and managed. Their theory suggests that the explanations should match the level of knowledge of the user, and explanations should be automatically, but unobtrusively provided, to the user (rather than the user expending cognitive effort to seek the explanations). Further, explanations should be provided in both feedforward (to facilitate task completion as the work is being done) and feedback formats (explanation of the rationale behind a decision outcome recommendation).

Anderson's (1990; 2000) Adaptive Character of Thought-Rational (ACT-R) theory of knowledge acquisition is the most commonly used theoretical basis for academic research looking at optimization of explanations (see Smedley and Sutton (2007) for a review). The most recent version of Anderson's theory (ACT-R) is reflected in Figure 1 (McCall et al. 2008). As noted earlier, the theory posits that knowledge acquisition is a sequential process where the earliest knowledge acquisition is at the declarative knowledge level (definitions, rules, examples), which is then proceduralized into advanced knowledge (procedural knowledge) that refines and tunes how this knowledge is used in the decision making process. The outcome eventually should be the formation of more formalized knowledge structures that mature over time as individuals begin to develop expertise.

The provision of explanations that match users' needs suggest that the type of explanation information provided should be associated with the knowledge level of the user—declarative knowledge for new decision makers (early novices), more rule-based and example oriented explanations as the novice becomes more experienced, and instructive explanations as the novice begins to build her knowledge base and proceduralize knowledge. This is consistent with the findings in Arnold et al. (2006) where novice accounting professionals (staff/seniors) selected more declarative explanations and feedforward explanations that explained how to complete the task. On the other hand, experienced accounting professionals (managers/partners) chose more feedback explanations that explained why the system was suggesting a course of action and what information was used to determine that course of action. This voluntary pattern of explanation use appears consistent with Anderson's (2000) theorizations and suggests automatic explanation provision building on a similar pattern should optimize knowledge transfer to a user, even when that user is focused on task completion and the actual work at hand.

This leads to the second hypothesis:

H2:   Professionals using a knowledge-based system that systematically
        provides explanations that build the users knowledge base will develop
        knowledge structures that are closer to that of an expert than will users of
        a system without such explanation provision.

Given that the two interventions (i.e., interface design and explanation provision) work in

different fashions to promote development of the user's knowledge structure, synergies should

arise from providing both. Prior accounting research demonstrates the benefit of providing a

cognitive frame to an accounting professional before task completion (Bonner et al. 1997;

Brewster 2011; O'Donnell and Schultz 2003; Schultz et al. 2010). If the interface intervention

using the expert knowledge structure is effective in transferring the knowledge structure to the

user, this should provide a cognitive frame that facilitates the accounting professional's

assimilation of the knowledge presented through the explanation facilities. Thus, the inclusion of

both interventions should facilitate more rapid development of more expert-like knowledge

structures than will the provision of either intervention alone. This leads to the third and final

hypothesis:

H3:   Professionals using a knowledge-based system with an interface
        resembling the knowledge structure of an expert and that systematically
        provides explanations that build the users knowledge base will develop
        knowledge structures that are closer to that of an expert than will users
        who receive only the interface or only the systematic explanation
        provision.

One caveat that should be considered regarding this latter hypothesis is a counter hypothesis that

suggests information load from all of the knowledge cues could actually overload a professional,

and this overload could interfere with knowledge acquisition (Gregor and Benbasat 1999; Rose

and Wolfe 2000).

METHODS

Research on expertise in accounting and auditing emphasizes the critical role of task

specific knowledge to expert decision making (Bonner 1990; Bonner et al. 1997). Even when the tasks are similar, if the environment (such as industry being audited) surrounding a decision varies, then expert knowledge structures may develop differently (Moroney 2007; Thibodeau 2003). These differences are particularly notable when the focus is on complex decisions that require sequential processing of multiple tasks, the decision making process is iterative in nature, and judgments involve multiple cognitive processes such as hypothesis generation, information search, and hypothesis evaluation. While complex decision processes such as in the professional accounting environment are difficult to study, these complex decision processes are the ones that provide the richest environment for studying expertise development and training interventions (Moreno et al. 2007). These complex environments provide challenges to the researcher, however, as defining and limiting the task environment to a level where specific experts can be identified can be difficult (Bonner and Lewis 1990; Libby 1995).

For the current study, the domain of insolvency was selected due to its highly specialized nature (Arnold et al. 2004b). Insolvency practice has existed internationally in many countries for close to a century and involve Certified Public Accountants/Chartered Accountants (CPA/CA) taking over management of a company that is facing financial distress (i.e., experiencing significant going concern issues) and evaluating the best alternative for the future of the company. Insolvency cases generally result in either a complete or partial liquidation, sell-off to another company, or reconstruction by the CPA/CA to restore the company to solid financial footing before returning operations to the prior directors and managers. Insolvency requires a great deal of expertise or the accounting firm/professional will not survive. In about half of cases, the CPA/CA assumes responsibility for losses incurred while operations continue under their direction and any such losses must be less than the fees they can collect in order to be

profitable (Arnold et al. 2004b). Poor judgment puts the firm/professional not only at legal risk, but also significant personal financial risk. Thus, insolvency decision making provides a solid foundation from which to explore expertise development and expert knowledge structures.

This study utilizes a 2 X 2 experimental design, with explanations manipulated as voluntary use vs. automatic provision and interface design manipulated as a generic map vs. expert knowledge map. The dependent variable is the closeness of the participants' knowledge map to that of an expert knowledge map.

Participants

Participants were recruited from the major international accounting firms, national firms with strong insolvency practices, and smaller boutique insolvency firms in Australia. The researchers requested that the firms send insolvency professionals with 1 to 3 years of insolvency experience[2] for three days of training on insolvency engagement decision making. The experience allows the participants to be familiar with the nature of insolvency engagements, but the training focuses on decision processes normally not an integral part of insolvency professionals' work until reaching at least 5 years' insolvency experience.

Seventy insolvency professionals participated in one of the training sessions, of which 67 completed the entire training.[3] Participants had a mean of 21 months insolvency experience, a mean age of 25, and an approximately even split between males and females. Of the participants, 64 percent were from the major international accounting firms, 33 percent from other national accounting firms, and 3 percent from local firms. All participants worked for firms in Australia where insolvency practice is a major component of accounting firms' practice.

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[2] Insolvency specialists generally have two or more years of general audit experience before moving into the insolvency specialization area.
[3] The knowledge mapping task was conducted at the beginning of training the first day and repeated at the end of training the third day. Three of the participants did not complete at least one of the knowledge mapping tasks.

Each three-day training session consisted of one of the four different treatments: voluntary provision of explanations with generic knowledge map interface, voluntary provision of explanations with expert knowledge map interface, automatic provision of explanations with generic knowledge map interface, and automatic provision of explanations with expert knowledge map interface. Because of the nature of the training, only one treatment could be conducted at a time. In other words, it was not feasible to conduct a session with multiple treatments as the training had to be specific to the particulars of the system being used. Information about each training session was provided to professional accounting firms throughout Australia. Firms voluntarily provided novice insolvency practitioners for the session most convenient for them. As a result, random assignment to treatments was not possible.

Experimental Task

The training sessions were based on a constructivist learning approach where the focus is on experiential learning (Crowe et al. 1996; Hannafin and Land 2000; Hirumi 2002; Jonassen et al. 2008). Constructivist-based training was ideal for the experimental process in that the training is focused on learning from actual experiences with engagement-like feedback throughout the process. Thus, the focus of the entire three days is on completing re-enacted insolvency cases with standardized feedback and use of the INSOLVE knowledge-based system.[4] No direct instruction is conducted by the instructors with the exception of describing the case-based learning tool and underlying approach at the beginning of the training, describing the INSOLVE system and its development process at the beginning of the training, announcing how to access

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[4] INSOLVE is a fully functional prototype expert system that mimics the decision making of expert insolvency professionals. The system has been extensively validated using numerous insolvency professionals including both professionals involved in the knowledge elicitation process and professionals independent of the development process (Leech et al. 1998, 1999). The functionality of the system has been extended in subsequent versions, most notably with the addition of explanation facilities (Arnold, et al., 2004a). The fully functional system has also been the subject of multiple prior accounting studies exploring how knowledge-based systems affect both expert and novice decision making as well as their interaction with the system (Arnold et al., 2004b, 2006).

and start each case, and debriefing the participants at the end of the three day training (post-experiment completion). Figure 2 provides a detailed overview of the experiment and the activities that took place on each of the three days.

[Insert Figure 2 about here]

The experimental process (i.e. training) was controlled through use of the INCASE system (Arnold et al. 2013). INCASE, which was developed to support constructivist learning, manages case delivery and allows content modules to be added and sequenced. INCASE allows the experimenter through a dashboard to control the sequence and timing of cases, keep participants synced in starting cases simultaneously, monitor progress, and record all participant activity. The system was used to provide a range of case information to the participants including video streams of interviews with clients, supplier, customers, and financiers; copies of key documentation from the actual engagements (masked so as not to allow identification of the actual insolvency engagement and people); financial statements; financial projections; and bid prices from potential suitors (see Figure 3 for a sample screen). Most cases had multiple stages where decisions to liquidate, sell, continuing operating, etc. had to be made at each stage. At the end of each stage, the participants would make a recommendation, enter information into INSOLVE and receive advice, revise their recommendation, document the reasoning behind their final decision, and then receive feedback from the engagement manager on how he had decided to move forward and his rationale. The explanation of decisions and the manager feedback were provided in accordance with normal engagement practice and in recognition of the important role that self-explanation (Bonner and Walker 1994; Earley 2001; 2003) and feedback (Earley 2001; 2003; O'Donnell and David 2000) have on expertise development. The use of self-explanation and provision of feedback were constant across all treatments.

[Insert Figure 3 about here]

On Day One, participants were introduced to the nature of the training process and the philosophies behind constructivist training. This was followed by completion of a pre-test of the knowledge mapping task for the company viability decision and collection of demographic information. The participants then completed a short case with specific written instructions on how to move through the case using the INCASE software. Next, participants completed two training cases using only the INCASE software. In the afternoon participants were introduced to INSOLVE, and they completed a standardized written tutorial on how to use the INSOLVE software by going back through the original INCASE practice case, but this time using INSOLVE to help complete the task.[5]

On Day Two, participants spent the day completing steadily more complicated cases with two cases in the morning and two cases in the afternoon. On Day Three, participants spent the morning session on two additional training cases. After taking a lunch break to remove them from the training focus, the participants completed a posttest knowledge mapping task for the company viability decision. This was followed by revisiting the two original cases they had completed without INSOLVE on Day One (again without INSOLVE). The third day ended with a debriefing session.[6]

INSOLVE: Knowledge-based System Interventions

The experimental treatments were induced through the use of alternative versions of the knowledge-based system INSOLVE. INSOLVE was re-programmed for our research to replicate

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[5] All training sessions were completed in an on-campus computerized classroom where each workstation had two monitors so as to alleviate the cognitive load in moving from the INCASE software to INSOLVE.

[6] Feedback during the debriefing was extremely positive from the participants with many noting how much better the training was with actually doing activities instead of listening to an instructor, and a consistent theme that doing the original cases the second time made it very clear to the participants that they had learned a substantial amount about insolvency practice during the training session as the cases were very simple to complete the second time.

versions from earlier research studies (Arnold et al. 2004a; 2004b; 2006; 2013; Leech et al. 1998; 1999). Our version of INSOLVE was programmed for delivery through a web browser and incorporated a researcher dashboard that allowed for deployment in alternative forms to specific participants. The INSOLVE interface was altered so that the questions that were automatically generated in earlier versions (information cues) were locked into a panel on the upper left of the screen, the explanation facility was locked into a panel on the lower left of the screen, and the right part of the screen provided a graphical representation of the information cues (see Figures 4 and 5).

[Insert Figures 4 and 5 about here]

Provision of Explanations

As in past versions of INSOLVE (Arnold et al. 2004a; 2006), explanations were available via selection and search. Despite the fact that feedback in the form of explanations is shown to increase performance, system users often will not seek feedback (O'Donnell and David 2000). Explanation systems generally receive minimal use if the user must exert effort to access the information (Arnold et al. 2006; Gregor and Benbasat 1999). Thus, we manipulated the provision of explanations as either available via voluntary selection (see lower left panel in Figure 4) or automatically provided (see lower left panel in Figure 5). The provision of explanations (H_2) was manipulated through the researcher dashboard for INSOLVE. The dashboard both controlled whether explanations would be automatically presented on the screen and the knowledge level of those explanations. INSOLVE provides both feedforward (to assist during actual task completion) and feedback (to explain recommendations) explanations. Additionally, from a knowledge component perspective, both modes of explanations provide four levels of explanation: definitions (basic declarative knowledge), rule-trace (more advanced declarative knowledge on how information cues are used in production rules), justification (more advanced

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declarative knowledge on examples and causal relationships between information cues), and strategic (procedural level knowledge documenting how decisions are derived by INSOLVE) (see lower left panel in Figure 4). For the automatic provision of explanations (see lower left panel in Figure 5), the system was coded as follows: (1) Definition Explanations for the INSOLVE training case and the morning session on Day Two training cases 1 and 2; (2) Rule Trace Explanations for the two cases in the afternoon of Day Two; and (3) Strategic Explanations for the two cases on the morning of Day Three. Thus, the level of knowledge explanation steadily increased for all participants in the automatic explanation provision manipulation in a manner consistent with Anderson's (2000) theory on knowledge acquisition (see Figure 1).

Knowledge Map Interface

The knowledge map interface for INSOLVE (H_1) was manipulated by using a generic map which displays the information cues in an alphabetical sequence (see Figure 5—enlarged with the 'zoom in' button) or as a composite expert knowledge map developed as described below (see Figure 4). The generic map with the alphabetical sequence used the same cues as the expert map so that it was not the display of information cues, but rather the visual organization that should drive any effects from the intervention.[7]

The expert knowledge map was developed using 25 information cues identified by Leech et al. (1998, 1999). Prior research indicates that at least 15 information cues are needed to develop a meaningful representation of experts' knowledge structures in complex decision domains (Rose et al. 2007; 2012). Leech et al. (1998, 1999) used 27 experts to develop, and 17

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[7] The choice of an alphabetical listing was deemed preferable to using a novice map organization as we were conducting actual training sessions for the firms. Thus, a negative condition would not have been ethically appropriate as it may have impaired their knowledge acquisition.

different experts to validate, an expert decision system that reliably mimics the decision making of insolvency experts. This system models an overall decision process involving assessment of the viability of an organization for purposes of deciding whether to continue or cease operations. Thus, the 25 information cues required for the decision environment are well-validated, exceed the number required for effective mapping of knowledge structures, and are representative of a complex decision environment with highly specialized experts. This decision model provides a solid basis for developing and validating the knowledge structures used to construct the expert knowledge map interface.

Pathfinder analysis is used to convert the expert ratings into a graphical model of an expert knowledge map that represents the composite knowledge structure of experts. Pathfinder network scaling provides a direct measure of a decision maker's knowledge structure, and Pathfinder-based measures of knowledge structures are predictive of performance, skill retention, and skill transfer (Choo and Curtis 2000; Day et al. 2001; Goldsmith and Davenport 1990; Kraiger et al. 1993; Schvaneveldt 1990). Rose et al. (2007) developed and tested a graphical method for measuring knowledge structures. Their approach allows participants to drag and drop concepts on a computer screen, and distances between every possible pair of terms are calculated and used to develop relatedness ratings.

The methods from Rose et al. (2007) were used to develop a software application that allowed expert insolvency practitioners to manipulate the 25 cues on a computer screen in order to determine their relatedness. Fourteen experts were given the instructions and drag/drop application presented in Figures 6 and 7. One of the researchers visited each expert in her office, trained her on the knowledge mapping software using an unrelated task associating different animals and animal characteristics, and then the expert completed the insolvency knowledge

mapping task while the researcher observed silently and then retrieved the data files.

[Insert Figures 6 and 7 about here]

The results of the pathfinder analysis indicates that the knowledge structures of the expert insolvency practitioners are highly similar (C = 0.588)[8]. This result is consistent with expectations, indicates that a single composite knowledge map is representative of insolvency experts' knowledge structures, and provides a valid model for building a knowledge map interface in an effort to facilitate knowledge transfer to a systems user. The expert knowledge map is shown in Figure 4.

Dependent Variable

On Day One, participants completed a pre-test of the knowledge mapping task for the company viability decision, prior to commencing the training. After completing the training on Day Three, participants completed a post-test of the knowledge mapping task. The dependent variable of interest was the closeness (C-score) of the novice insolvency professional's posttest knowledge map to that of the composite expert knowledge map for the company viability decision. The pre-test C-score was used as a covariate to control for any initial differences in knowledge.

RESULTS

Table 1, Panel A provides the descriptive statistics for the C-scores by group. Figure 8 graphically presents the posttest results. There are notable changes in the mean posttest C-scores for participants when the interventions are made available in the knowledge-based system. Those participants receiving neither intervention have a mean posttest score of .197. Just providing the knowledge map interface raises the mean to .272 and just automatically providing explanations

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[8] C-scores can range from 0 to 1, with a score above .300 considered as representing strong agreement in knowledge structure.

raises the mean to .248. When both interventions are present, the mean is .274, which is

approaching the .300 threshold that indicates consistency with the expert knowledge maps.

[Insert Table 1 and Figure 8 about here]

The change in pretest to posttest C-score is perhaps even more interesting. Those

participants receiving neither intervention actually worsened in the posttest (-.015), while there

are gains of .018 (automatic provision of explanations), .024 (expert knowledge map interface)

and .036 (both interventions) in consistency of knowledge maps for the three intervention

treatment groups.

Table 1, Panel B provides the results of the ANCOVA analysis.[9] The ANCOVA analysis

is conducted using the posttest C-score as the dependent variable, explanations (voluntary use vs.

automatic provision) and interface design (generic map vs. expert knowledge map) as the

independent variables, and the pretest C-score as the covariate.

H1 predicts that the provision of an expert knowledge map interface design for the

knowledge-based system will help the user develop more expert-like knowledge structures. The

mean values indicate that by providing the expert knowledge map interface as opposed to the

generic knowledge map interface, the participants mean posttest C-score rises from 0.229 to

0.273. The main effect for the knowledge map interface is significant at p=0.01.

H2 predicts that the automatic provision of explanations within a knowledge-based

system will help the user develop more expert-like knowledge structures. The mean values

indicate that by providing automatic explanations in a knowledge sequenced fashion as opposed

to only providing them in a voluntary use form results in the participants mean posttest C-score

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[9] Because of unequal cell sizes a Levene's test for homogeneity of variance was conducted and the results indicate that the variances are not unequal (p=.98) supporting the use of the ANCOVA analyses.

rising from 0.236 to 0.261. The main effect for the automatic provision of explanations is significant at p = 0.10.

H3 predicts that the greatest development of expert-like knowledge structures will occur when the system is designed to provide both the knowledge map interface and the automatic explanation provision. The results of the planned contrast (-1, -1, -1, +3) as shown in Table 1, Panel C, support H3 (p=.05). However, while the mean value for the C-scores is highest when both interventions are present, an additional contrast test confirms that the participants mean posttest C-scores of .274 is not significantly greater (p=.96) than providing the knowledge map alone (C=.272).

CONCLUSIONS

This study addresses a potential conflict between the efficiency and effectiveness gains that are perceived to arise from the use of standardized audit support systems and other knowledge-based systems for accounting professionals (Banker et al. 2002; Bedard et al. 2008; Dowling 2009; Dowling and Leech 2014) and the potential deskilling effects from use of such systems (Arnold and Sutton 1998; Arnold et al. 2004b; Dowling et al. 2008; Dowling and Leech 2014). We specifically examine two potential system design interventions that may help ameliorate the potential deskilling effects—use of an interface layout that mimics experts' knowledge structures and the automatic provision of knowledge-based explanations during task completion.

This study was conducted in order to systematically work towards an effective training intervention for use in knowledge-based systems for professionals. We use a knowledge map developed from 14 expert insolvency professionals to design an interface and test for its usefulness in facilitating user development of expert-like knowledge structures. Additionally,

knowledge-based explanations are automatically provided to the novice accounting professional during task completion in order to both facilitate task completion (feedforward explanations) and to assist the professional in assessing decisions (feedback explanations). The results of the study indicate that both interventions have a significant effect on novice professionals who use knowledge-based systems. Surprisingly, the combination of the two interventions provides only a very small difference in expert-like knowledge structures when compared to the incorporation of only the expert knowledge map interface. This may result from cognitive overload created by a complex interface combined with required evaluation of explanations, and further research will be needed to determine whether and how the design features could be combined to enhance expertise development.

The results of this research are important to both theory and practice. From a theoretical standpoint the research suggests that technology dominance effects such as deskilling can be addressed, at least in part, by considering how such systems are designed. While expert knowledge map based interfaces may not seem as intuitive and user friendly, the longer term benefits may justify a greater emphasis on alternative interface designs. Further, most existing systems are built around the use of help facilities that require the user to extend cognitive effort to seek and identify explanations that facilitate effective system use. Our research shows that when such explanations are automatically presented in a format that better matches the knowledge level of the expert, they are more effective for promoting expertise development than are passive explanation facilities requiring the user to seek help.

There are limitations to the study that should be considered when assessing the results. First, our sample is relatively small. The requirement for participants to sit through three consecutive days of training at an offsite location placed a burden on participation, even though

the reaction to the training was very positive and well received by participants. However, the long-term nature of our training task allowed us to avoid a weakness common to most studies that have examined the effects of system design features on users. Most prior studies involve experiments with very brief use of a system during one session. Second, our research seeks to understand the effects over time of system use, but condensing multi-week engagements into sessions generally lasting about two hours does potentially diminish the actual effects of knowledge-based system use over an extended period of time. Nonetheless, we were able to put participants through six engagements in an accelerated fashion while using the knowledge-based system on a constant basis. The use of constructivist training in other domains have been effective for rapidly developing experience based knowledge, but whether it also expedites the actual effects from knowledge-based system use is uncertain. Third, prior research suggests that knowledge structures are critical to providing the frame for storing knowledge components (Kopp & O'Donnell 2005). Thus, the short duration of the experimental treatments may have allowed the development of expert knowledge structures to develop more quickly, but not have provided the additional time necessary for categorizing the explanation knowledge within those structures. Thus, the effect of the explanations may be stronger over a longer period of time using the system.

There are also implications for future research. First, this research initiates a discussion on how systems can be better designed to counter the potential effects of deskilling on professionals using such systems. Future research should consider other such potential interventions that could mitigate at least in part these potential deleterious effects. Second, the research raises questions about the viability of active versus passive support such as that found in explanation (i.e. help) facilities embedded in systems. The research here has assumed a

sequential pattern of knowledge matching explanations with user knowledge base without assessing differences in individual users (i.e. all users received the same progression of explanations). Future research should consider how systems can assess users' current knowledge state in order to better tailor explanations and other systems help for those users. Finally, while this research identifies interventions in which accounting professionals can improve acquisition of expert-like knowledge structures, our understanding of the degree of deskilling effects that arise from technology use are still very limited. The risk of deskilling is great for the profession and garnering a better understanding of how and to what degree deskilling is occurring is a critical research issue that needs greater attention.

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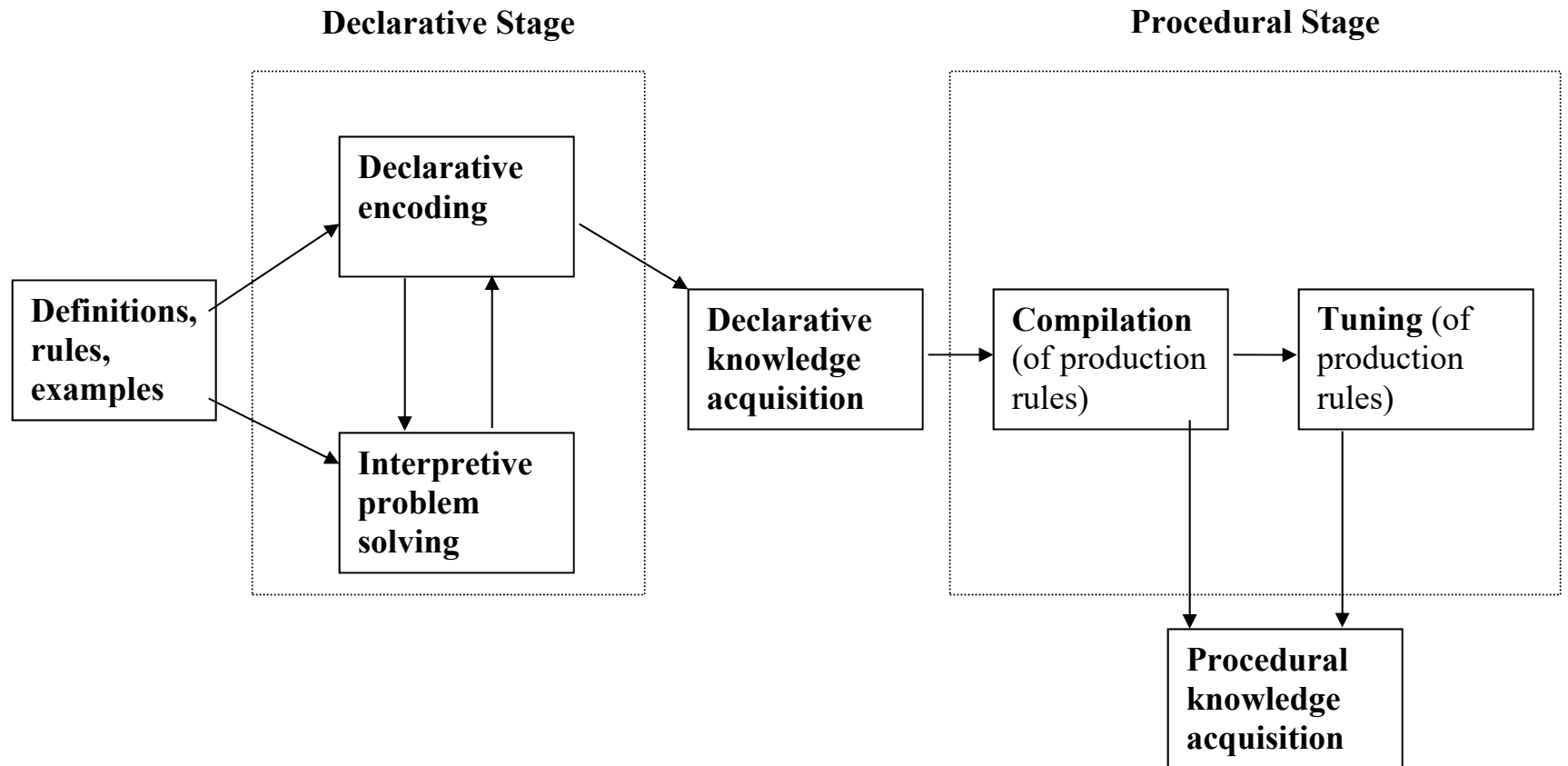
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FIGURE 1
Stages of Individual Knowledge Acquisition

Declarative Stage   **Procedural Stage**

```
┌─────────────────────────────────────┐   ┌──────────────────────────────────────┐
│         ┌──────────────┐            │   │  ┌──────────────┐  ┌──────────────┐  │
│         │ Declarative  │            │   │  │ Compilation  │  │ Tuning (of   │  │
│         │ encoding     │            │   │  │ (of          │→ │ production   │  │
│  ┌──────┐─────┐        │            │   │  │ production   │  │ rules)       │  │
│  │      │     │        │  ┌─────────┐│  │ rules)       │  │              │  │
```

Definitions, rules, examples → Declarative encoding → Declarative knowledge acquisition → Compilation (of production rules) → Tuning (of production rules)

Declarative encoding ↕ Interpretive problem solving

Compilation (of production rules) → Procedural knowledge acquisition ← Tuning (of production rules)

Definitions, rules, examples

Declarative encoding

Interpretive problem solving

Declarative knowledge acquisition

Compilation (of production rules)

Tuning (of production rules)

Procedural knowledge acquisition

Reproduced from McCall, Arnold, and Sutton, 2008

FIGURE 2
Overview of Experiment

```
┌─────────────────────────────────────────────┐
│        Overview and Informed Consent          │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│         Pathfinder Concept Mapping            │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│      Demographic and Knowledge Questions      │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│    Case Delivery System (INCASE) Training     │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│     Completion of Case 1 and 2 without KBS    │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│    KBS (INSOLVE) Training with Training Case  │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│  Refresher Training on INSOLVE and INCASE     │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│     Completion of Case 3, 4, 5, 6 with KBS    │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│      Completion of Case 7 and 8 with KBS      │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│         Pathfinder Concept Mapping            │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│     Completion of Case 1 and 2 without KBS    │
└─────────────────────────────────────────────┘
                      ↓
┌─────────────────────────────────────────────┐
│                  Debriefing                   │
└─────────────────────────────────────────────┘
```

Day 1 — (Overview and Informed Consent through KBS (INSOLVE) Training with Training Case)

Day 2 — (Refresher Training on INSOLVE and INCASE through Completion of Case 3, 4, 5, 6 with KBS)

Day 3 — (Completion of Case 7 and 8 with KBS through Debriefing)

FIGURE 3
INCASE Case Delivery System

FIGURE 4
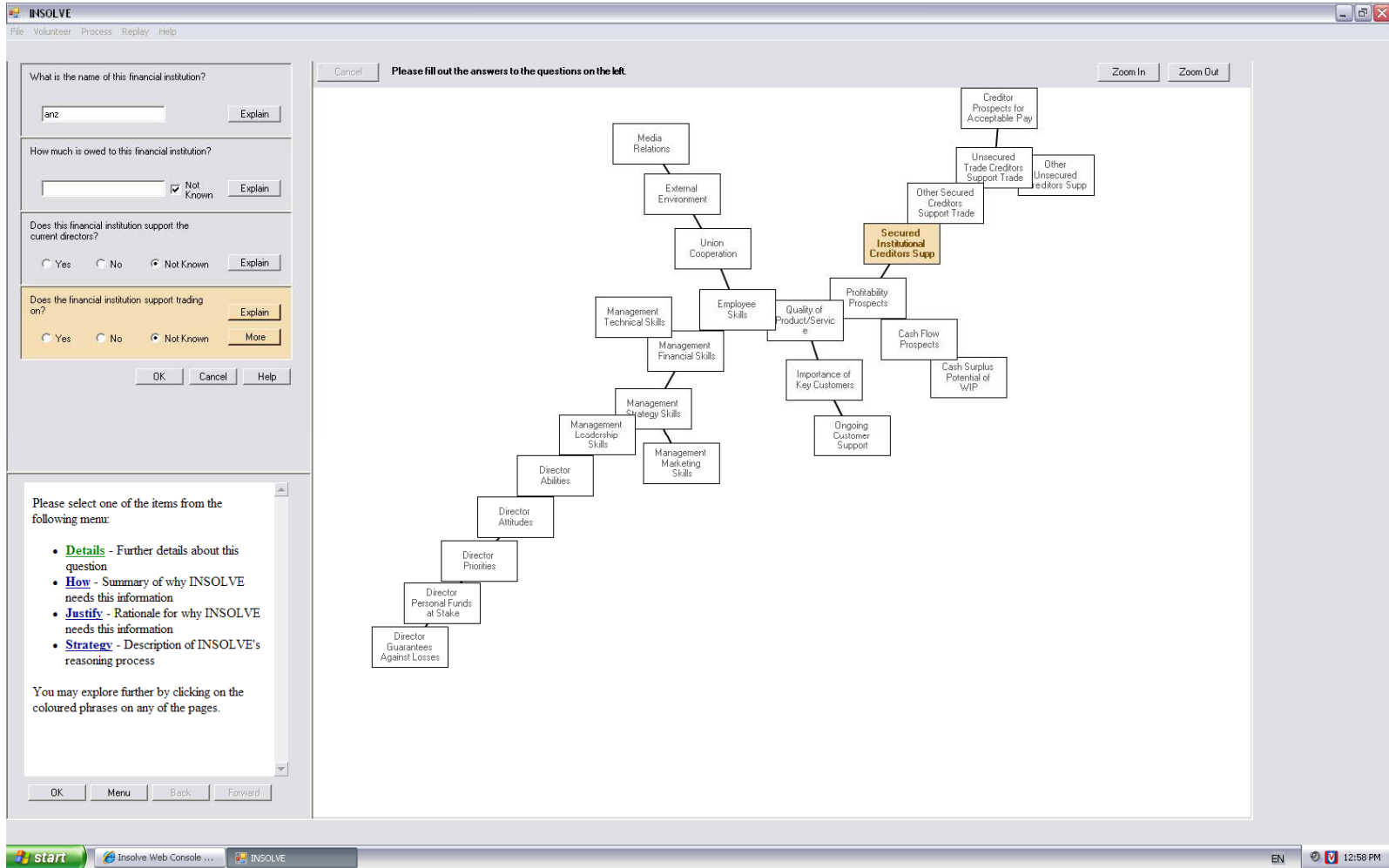**INSOLVE System with Knowledge Map Interface and Voluntary Explanation Access**

FIGURE 5
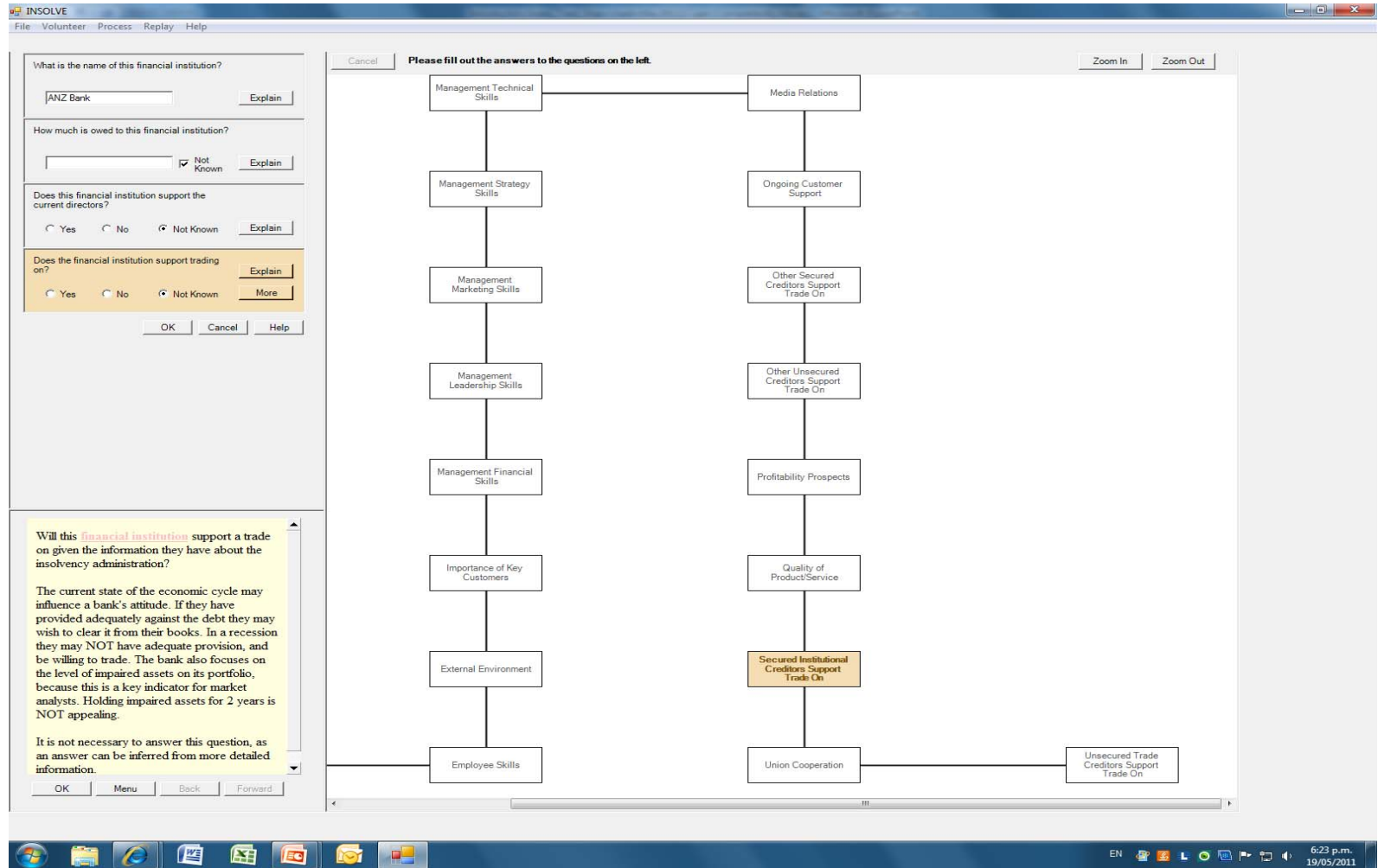**INSOLVE System with Alphabetic Cue Interface and Automatic Explanation Provision**

Figure 6
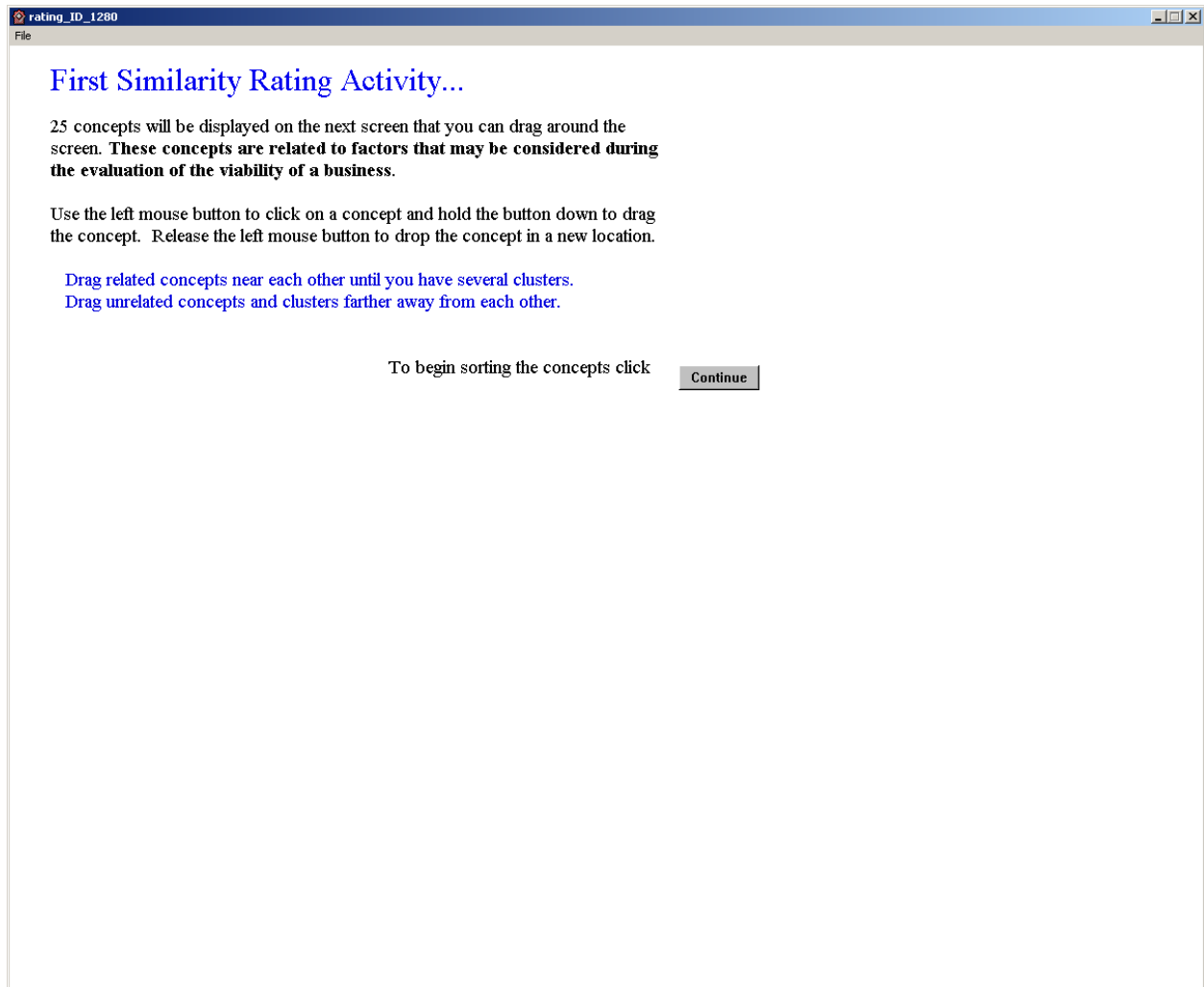**Instructions for Expert Insolvency Practitioners**

Figure 7
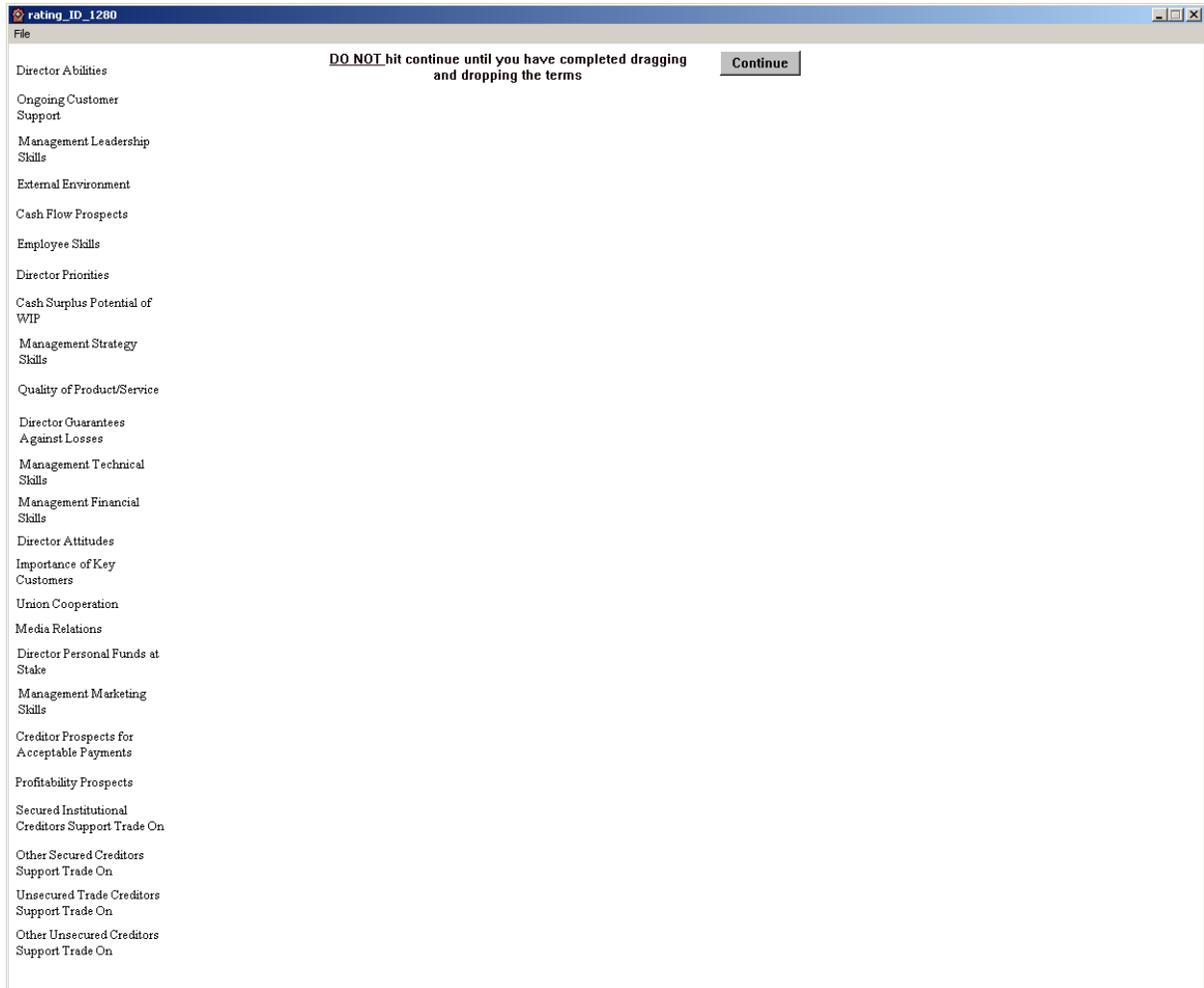**Software that Allows Users to Drag and Drop Concepts to Represent their Relatedness**

Figure 8
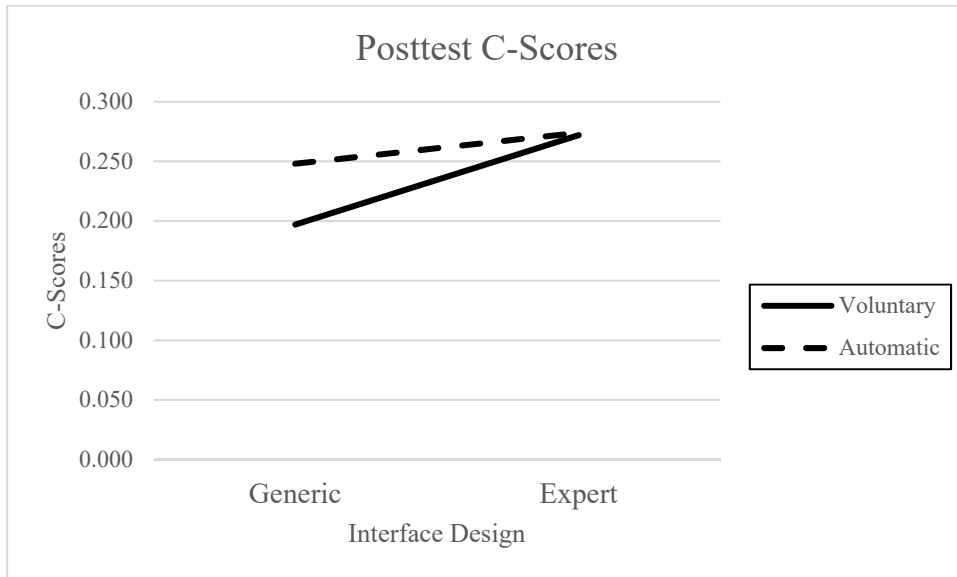**Graphical Display of Posttest C-Scores by Condition**

TABLE 1
Results of Hypotheses Testing

Panel A: Descriptive Statistics for Final Knowledge Structure

	Generic Knowledge Map	Expert Knowledge Map	Total
Voluntary Provision of Explanations			
n	12	13	25
Mean	.197	.272	.236
St. Dev.	.087	.077	.089
Change (Final – Initial)	-.015	.024	.005
% Change	-7.1%	9.7%	2.2%
Automatic Provision of Explanations			
n	20	22	42
Mean	.248	.274	.261
St. Dev.	.080	.079	.080
Change (Final – Initial)	.018	.036	.028
% Change	7.8%	15.1%	12.0%
Total			
n	32	35	67
Mean	.229	.273	.252
St. Dev.	.085	.077	.083
Change (Final – Initial)	.006	.032	.019
% Change	2.7%	13.3%	8.2%

Panel B: ANCOVA for Final Knowledge Structure

Source	SS	df	F	p-value
Model	.087	4	3.636	.01
Intercept	.268	1	44.702	< .01
Interface Design	.030	1	5.030	.01
Explanations	.010	1	1.651	.10
Knowledge Map Interface * Explanations	.007	1	1.131	.15
Covariate Knowledge Structure (Initial)	.036	1	44.702	< .01
Error	.372	62		
Total	4.714	67		

Panel C: Planned Contrasts

Contrast	df	t-value	p-value*
Cell 4 > Cells 1, 2, 3 (+3, -1, -1, -1)	63	1.633	.05

*one-tailed