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ABSTRACT

When attempting to evaluate expertise, it is important to assess not only what individuals know but also how they organize that knowledge. Numerous methods have been proposed for deriving graphical representations of knowledge organization, or mental models, but not enough is known about the relative effectiveness of these methods. Structural assessment (SA) and revealed casual mapping (RCM), two methods for capturing mental models, are compared according to their ability to assess student learning of object-oriented (OO) concepts. The study follows undergraduate students learning Visual Basic.NET (VB.NET), assessing their mental models at the beginning and end of the semester and comparing the similarity of students' organization of knowledge to that of OO experts. Findings from this study will add to the body of knowledge on mental models, and may be used to develop more effective teaching content and structure.

Keywords

Object-oriented concepts, mental models, revealed causal mapping, structural assessment

INTRODUCTION

IS personnel are constantly faced with fundamental shifts in methods, technologies and mindsets. When such a shift occurs, individuals will typically first learn the conceptual knowledge associated with the new mindset and then attempt to organize that knowledge. Within the domain of software development, previous research (e.g., Tapscott and Caston, 1993) has determined that learning during a shift in mindset is more difficult than traditional, incremental learning. One possible reason for this difficulty is the fundamental change in conceptual knowledge associated with the transition to the new software development approach. In addition, these newly acquired concepts must be organized into mental models.

Previous literature has indicated that learning the semantics or concepts of a programming language prior to the introduction of the language syntax increases performance (e.g., Dyck and Mayer, 1989). This study will provide insight into the process by which students learn not only the concepts of a software development approach but also how they organize that knowledge. As such it represents an important step and should provide us clues to improve the learning process. While there has been much research investigating the transition to object-oriented software development (OOSD), there are relatively few studies that investigate the underlying mental model of OO knowledge and the development of expertise. This paper addresses the gap by focusing on the cognitive representation of knowledge development in OOSD. Two research questions will be addressed by this project: 1) how do students learning OOSD concepts organize that knowledge, and 2) what is the best method to capture a representation of their knowledge organization?

To understand how students learn a new software development approach, we need to determine the appropriate method to capture this information. In recent years, revealed causal mapping (RCM) has enjoyed a great deal of popularity in empirical research among cognition-oriented scholars. Although some methodological properties of RCM have come under scrutiny, one fundamental question remains unanswered: How do the data yielded by these techniques compare with the data obtained by other methods? Without works comparing alternate methodologies, we cannot be fully confident of the meaning of the data yielded by causal mapping. Structural assessment (SA) is another technique that has been used to understand the cognitive changes that occur during the learning process. While SA has been compared to some other techniques, it has not been compared to RCM. This research empirically compares these two methods of assessing mental models to determine which one more accurately captures changes in students' domain knowledge over a learning event.

BACKGROUND

Learning Software Development

When teaching software development, the sequence in which the material is presented has an impact on the students' learning. General findings on software development support the notion that students who learned semantics first and then syntax, performed better than students who learned both simultaneously (Bayman and Mayer, 1988; Dyck and Mayer, 1989). Within the OO mindset, it appears even more important to focus on learning the conceptual, design and modeling aspects prior to the introduction of coding (Crews and Butterfield, 2003; Hardgrave and Doke, 2000; Nelson, Armstrong and Ghods, 2002). Thus, when learning a new software development mindset, initial training efforts should be focused on understanding the conceptual aspects of the mindset.

Mental Models

Conceptual knowledge is the knowledge of concepts, events, or objects in a domain. Concepts have been defined as the actual ideas and information embodied in the knowledge (Ausubel, 1963, p. 76), or as perceived regularities in events or objects, or records of events or objects designated by a label (Novak, 2002). Schemata (originally proposed by Bartlett, 1932) are active processes that continually evaluate incoming information to determine if it is relevant (Relmann and Chi, 1989) and how it should be associated with previously acquired knowledge. Other names for schemata include: knowledge structures, mental models, conceptual frameworks, cognitive structures, cognitive maps, and frames (Day, Arthur and Gettman, 2001; Gagne, 1985; Glaser, 1990; Johnson-Laird, 1983; Rouse and Morris, 1986). For consistency, the term 'mental model' is used hereafter to represent this concept.

Scholars in a variety of areas have studied the impact of mental models on learning (e.g., Davis and Yi, 2004; Day et al., 2001). A consistent theme across these studies is the correlation between knowledge acquisition, mental models and performance. As learning occurs, novices whose mental models show a higher degree similarity to those of experts are found to perform better when their knowledge is assessed with other methods. These studies establish the importance of the connection between existing mental models and the acquisition of new knowledge. It appears that expertise is not just a function of the volume of knowledge, but also a way of thinking about the problem, based on how that knowledge is organized (Vitalari, 1995). This leads to our first two hypotheses:

> H1: The similarity of students' mental models to experts' mental models will increase over the course of the semester.

> H2: Greater similarity between student and expert mental models will be associated with higher course grades.

Revealed Causal Mapping

Revealed causal mapping (RCM) is one of a collection of causal mapping techniques used to elicit and analyze the structure and content of cognition (Axelrod, 1976). It is a qualitative research method that is consistent with an exploratory research setting, can be used to elicit group level cognition (e.g., Narayanan and Fahey, 1990) and has been successfully used in a software development context (Nelson, Nadkarni, Narayanan and Ghods, 2000). In this study, we conducted interviews with students in a VB.NET course and used RCM to create a cognitive representation of interlinked concepts embedded in the students' knowledge of the concepts of OO software development. Readers interested in the details of this process are referred to Narayanan and Fahey (1990) and Nelson et al. (2000).

Structural Assessment

Structural assessment (SA) is a technique for capturing and assessing mental models, which uses respondents' ratings of the similarity between pairwise comparisons of key concepts within a knowledge domain. The Pathfinder algorithm is used to derive a graphical representation of a mental model from the relatedness ratings. SA has successfully been used to assess learning in a number of related domains including electronic spreadsheets (Davis and Yi, 2004) and computer programming (Acton, Johnson and Goldsmith, 1994). The OO concepts (e.g., class, attribute, polymorphism) used in this technique were derived from a review of the OO literature; students were asked to complete a survey in which they assessed the relatedness of all possible combinations of pairwise comparisons.

We believe that both RCM and SA will prove effective techniques for assessing the changes in student's mental models over the course of the semester. However, we do believe that there will be some differences in the applicability of the techniques to the setting in which they are used. In this case, the members of the group being assessed are undergraduate students, most of whom are seeing their first introduction to OO concepts within the context of a VB.NET programming course. While they will gain some familiarity with OO concepts, we do not expect that they will gain sufficient expertise to form sophisticated mental models of these concepts. Thus we expect that the students may be able to articulate the meaning and/or usage of

some of the basic OO concepts without being able to articulate the exact terms. For example, the student may be able to explain that you create a customer who gets his/her characteristics (attributes and methods) from the customer class without using the term 'object'. In contrast we expect the students to be less able to connect the concepts with only the concept labels provided (e.g., object and class). We expect that RCM, which depends on an interview procedure for knowledge elicitation, will better capture the incremental or finely grained changes in students' expertise.

> H3: Both RCM and SA will reflect changes in student expertise over a learning event.

> H4: RCM will better capture incremental changes in student expertise over a learning event.

METHOD

Undergraduate students learning VB.NET programming constitute the sample for this research. For both the RCM and SA techniques, observations will be made at the beginning and end of the semester. Expert referent structures are necessary for comparison; in both cases we will use aggregated responses from OO experts. Students' mental models will be compared to the expert structures by computing a measure called *similarity*. This is a set-theoretic measure that compares two maps of mental models by taking the ratio of the number of links in common between the maps to the total number of links in the two maps (Gomez, Hadfield and Housner, 1996). A significant increase in similarity between student and expert maps over the course of the semester will support H1. We will also use similarity to assess H2; we expect that students whose mental models more closely resemble those of the experts should also earn higher grades. A regression model showing a significant positive relationship between similarity to expert structures and students' course grades should support H2. H3 will be supported if both RCM and SA methods demonstrate significant changes in similarity over the course of the semester. H4 will be supported if the relationship between similarity and course grades is stronger for RCM than for SA.

PRELIMINARY RESULTS AND IMPLICATIONS

The first wave of data collection has been completed and preliminary analysis is underway. Data has been collected on 75 students with 37 participating in the RCM method and 38 in the SA method. 67% of the students are male and their academic majors are primarily information systems (52%) and industrial engineering (33%). Our initial results suggest that, as expected, student's beginning mental models show little organization and little similarity to either other student's mental models or to expert mental models. As we proceed with the second phase of data collection and analysis, we hope to see both greater levels of organization in students' individual mental models and greater similarity between students' and experts' mental models.

Several theoretical implications can be drawn from this study. First, our understanding of the cognitive representations of students learning OO software development will be enhanced. This study identifies the knowledge that characterizes learning OO software development and how that knowledge is organized. Second, this study identifies and compares the cognitive representations of methods of knowledge elicitation.

This research also offers managerial implications. Both universities and organizations can use the maps evoked in this study to design learning materials and techniques that anticipate problems with learning OO concepts and overcome them before they become obstacles. The use of cognitive maps as a tool for teaching has shown positive results (e.g., Brown and Stanners, 1983). Future research may test teaching student developers the OO approach by focusing on developing a mental model for the learner that mirrors the OO expert mental model.

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