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THE EFFECTS OF LEARNING STYLES AND MODELING TECHNIQUES ON REQUIREMENT DOCUMENTATION PERFORMANCE

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ABSTRACT

The present study examines the effect of Individual Learning Style on modeling functional requirements. To-date, there is no evidence that individual cognitive learning styles are related to modeling ability in novice systems analysts. The results of this study indicate that in teaching functional requirement techniques, novices with abstract learning styles perform as well as those with concrete learning styles.

Keywords

Cognitive Style, Learning Style, Use Cases, Functional Decomposition Diagrams.

INTRODUCTION

The main focus of this work is on evaluating the effect of an individual's cognitive learning style on representing systems requirements. Two modeling techniques, namely functional decomposition (FD) model and use case (UC) model, are the two most widely used requirement-modeling methods. The software engineering research community has been debating what modeling techniques are the best to develop software systems. Current literature has divergent views on this issue. This study will provide some empirical evidence to compare between process-oriented and object-oriented modeling techniques. In addition, it introduces a new contingency variable, learning style, into the information systems development literature.

THEORETICAL BACKGROUND

Following the framework for research on conceptual modeling (Wand and Webber, 2002), in this paper we focus on investigating the effect of individual differences factor on systems requirement modeling.

Vessey and Conger (1994) discuss the issue of application and methodology knowledge as essential elements of systems development. They investigate the influence of the interrelationship of these elements (experience with the application and knowledge of the methodology) on performance in the information requirements specification process.

Their study indicates that once ability to apply a methodology has similar effect on the effectiveness of specifying information systems requirement as once familiarity with the application. Their work has a major implication on the type of skills needed for system development, specifically, whether it is better to train people in systems development methods or in the functional area under investigation. This issue is relevant for systems development by end-users.

In the present study, the focus is on the effect of individual learning style on specifying information requirements, as a result; the application knowledge is not relevant since there is only one domain. Thus, the focus is on the issue of methodology knowledge.

A number of studies have examined the methodology knowledge in relation to requirement specification during systems development (Leitheiser and March, 1996; Morris et al.,1999; Nelson and Millet, 2004; Sheetz et al, 1997; Topi and Ramesh, 2002) but none have investigated whether a particular way of learning influences performance when using a particular method. Up-to-date, there is no evidence that individual cognitive learning styles are related to modeling ability in novice systems analysts.

Modeling Techniques

In the structured methodology approach, Functional Decomposition is one of the most commonly used techniques for analysis. A functional decomposition diagram (FDD) is a top-down representation of business functions and processes. It is the deliverable of the functional decomposition process, which breaks the functional description of a system down into small components. Using an FDD, an analyst can show business functions and breaks them down into lower-level functions and processes.

Use cases are one of the most important elements of object-oriented analysis and design for organizing user requirements. A use case is a description of set of sequences of actions that a system performs that yields an observable result of value to a particular actor. A use case diagram includes a set of use cases and actors, and the relationships between them. An actor is a person or a system that derives benefit from and is external to the system. Each use case is described in detail. Use cases are the primary drivers of UML diagramming techniques.

Cognitive Learning Styles

Kolb's experiential learning (Hawk and Shah, 2007; Kolb, 1984, Kolb 1985) is a theory of cognitive learning styles. Kolb identifies two main dimensions of the process by which people learn. The first dimension, the concrete-abstract continuum, is the way we perceive new information. In new situation, some people prefer to sense and to feel their way (Concrete Experience) while others prefer to think their way through (Abstract Conceptualization).

The second dimension, the active-reflective continuum, is how we process new information. Some people prefer to jump in and try things (Active Experimentation) while others prefer to process new information by reflecting on it (Reflective Observation).

According to the theory, the extremes of each dimension are mutually exclusive. If we try to simultaneously perceive new information, for example, by Concrete Experience and by Abstract Conceptualization, a conflict situation will arise. To resolve the conflict, each individual must choose how to perceive the new information and how to process it. Therefore, each individual develops a preference, that is, a learning style, to perceive and process new information.

Kolb's theory predicts that students with different learning styles will respond differently to various teaching methods and that instructional strategy should match the learning styles of students. Individuals with different learning styles tend to learn differently from different teaching methods. Some students may grasp abstract concepts readily while others need concrete imagery to learn. There appears to be some connection between the conceptual models and the concrete-abstract dimension of learning styles. Individuals with an abstract learning mode tend to discover the rules and structures inherent in an abstract model. These individuals take an analytical conceptual approach to learning. Individuals who prefer a concrete learning mode take an experiential-based approach to learning. Therefore, the concrete model seems more appropriate.

There is evidence (Bostrom et al., 1988) that abstract learners benefit more from an abstract model and are hampered by the concrete model. Concrete learners, on the other hand, benefit more from a concrete model. The active-reflective dimension of Kolb's learning style deals with active involvement aspects in learning and is less related to any interaction with the provided conceptual models. This dimension was not investigated further in this study.

THEORETICAL MODEL AND HYPOTHESES

The purpose of this study is to answer the question: which of the two modeling techniques (Functional Decomposition or Use-Case) will best help novice systems analyst with different cognitive learning styles (Concrete or Abstract) model system requirements? Therefore, the research questions and hypotheses for this study are:

Modeling Techniques Effects

Q1: Is use-case modeling technique better than functional decomposition technique in helping systems analysts to produce more complete system requirement specifications?

H1: There will be no difference in performance score between the Subjects using the Use Case technique and the subjects using the Functional Decomposition technique.

Learning Styles Effects

Q2: Do systems analysts with an abstract learning style outperform systems analysts with a concrete learning style in systems requirement specification?

H2: Subjects' Learning Style does not influence the Performance of Subjects.

Interaction Effects

Q3: Do systems analysts with a concrete learning style perform better when using a use-case modeling technique?

Q4: Do systems analysts with an abstract learning style perform better when using a functional decomposition modeling technique?

H3: There is no significant interaction effect between modeling technique and learning style on the performance of subjects.

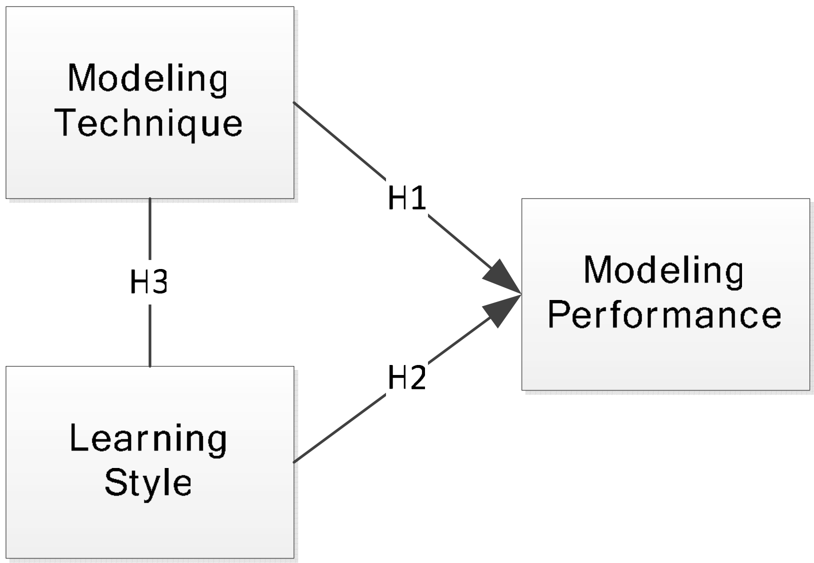

Figure 1. Research Model

METHODOLOGY

An experimental research design was implemented to study the research questions. The design was a 2 by 2 factorial design with 2 independent variables: modeling technique and learning style. Twenty nine graduate students enrolled in a Systems Analysis and Design class at a major southeast research university served as the subjects for this study. Each subject was randomly assigned to either a Functional Decomposition technique group or a Use-Case diagrams group. Within each modeling group, subjects were identified as either abstract learners or a concrete learner based on their scores on the Kolb's Learning Style Inventory (Kolb, 1985).

We used completeness as criteria to evaluate the quality of the diagrams produced using the two modeling techniques. A diagram is complete if no required element (a function or a use case) is missing when compared to a standard developed by the researcher from requirements specifications described in a case (Wand and Weber,2002;Wand and Weber 1994, Yadav et al,1988). Each diagram was scored on a scale of 0 to 100.

Experimental Procedure

Before the experiment, all subjects completed a learning style inventory. Then, subjects were divided into two different groups. One group was taught in functional decomposition modeling. The other group was taught in use case modeling. Standard lecture scripts were used to teach these two different groups.

Specifically, the students received a half-hour lecture on use cases, which included discussion of a sample problem, the use case description as well as the use case notation. Then students were given enough time to develop a use case diagram to describe the complete system.

There was a nominal reward applied toward the course grade for each completed and returned exercise. Exercises collected were compared to a set of standard "solutions." The result of the comparison will be used as performance measure.

RESULTS AND DISCUSSION

A total sample of 29 subjects participated in the experiment. The proportion of participants according to modeling technique was 48% and 52% for the functional decomposition and use-case technique, respectively. The proportion of subject's learning style was 66% of abstract learners and 34% for concrete learners.

The mean of the performance measurement (completeness) was 68.6 and 44.7 for the functional decomposition and use-case technique, respectively. On the other hand, average performance score was 52.4 and 63.6 for abstract learners and concrete learners, respectively.

Source of Variation	Type III Sum of Squares	df	Mean Square	F value	Prob>F
Modeling technique (A)	**3175.361**	**1**	**3175.361**	**15.662**	**0.001**
Learning Style (B)	**59.493**	**1**	**59.493**	**0.293**	**0.593**
A*B Interaction	**35.087**	**1**	**35.087**	**0.173**	**0.681**

Table 1. Analysis of Variance Table for Student's Performance

Table 1 reports the results of the Analysis of Variance (ANOVA). The F-value for the modeling technique factor was 15.662, which is statistically significant ($p < 0.05$), indicating a significant difference on performance scores between the functional decomposition and use-case modeling techniques Thus, hypothesis H1 was rejected.

The learning style factor was not statistically significant ($p > 0.05$), indicating no significant difference on performance scores between the two learning style groups. No significant interaction effect is present between the two factors. The F for interaction was 0.173 and was not statistically significant indicating that there is no significant relationship between modeling technique and learning style. Thus, hypotheses two and three were not rejected (H2 and H3). This paper investigates the effect of modeling technique with learning styles on modeling performance. Modeling performance was measured as a function of subjects' models completeness. The results reported in this study provide some interesting discussion. The modeling technique demonstrates a stronger effect than learning styles with modeling outcomes. In addition, it was found that subjects learning style does not relate to modeling performance.

Although this study does not provide evidence for the effect of individual learning style on the performance of novice students, caution should be taken when designing instruction (Csapo and Hayen, 2006). The lack of significant learning style effect on student performance could be attributed to the sensitivity of Kolb's learning style inventory measure used in this study. It is recommended that other individual characteristics be used to understand the difficulties when specifying systems requirements.

Previous studies have indicated that students commonly have difficulties in documenting systems requirements using either object-oriented or structured techniques (Nelson and Millet, 2004; Vessey and Conger, 1994).

Clearly, there are some limitations in the present study that must be addressed. First, when studying an individual learning style, it is important to consider the complexity of the study domain as well as the experience level. In this study, we did not test for type of problem domain and experience effects on system modeling. Thus, it is recommended that similar type of studies be implemented using different domain context and level of experience. Second, the time provided to the subjects in order to complete the models could have been a factor affecting the performance of the students.

Third, attitudinal measures such as confidence in solution accuracy and perceived ease of use were not considered. And fourth, one should consider using multivariate measures of scoring the system models created (grading scheme) such that a criteria includes evaluation of syntax and semantic characteristics. Thus, future experiments would benefit from using correctness, and comprehension questions.

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