Can A Single Exposure To The Resource-Event-Agent Framework Enhance Data Modeling Performance?

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ABSTRACT

Due to the widespread use of technology, it is becoming increasingly critical that accounting students have the ability to document accounting information systems (AIS). This skill is important for understanding the information system, mapping business processes, and understanding systems' controls. The present study reports on an experiment designed to investigate the effects of a single exposure to the Resource-Event-Agent (REA) framework on students' data modeling performance. The results of the experiment indicate that accounting students who receive a single, scripted exposure to the REA framework perform better on data modeling tasks than students with no exposure to the REA framework. This has important implications for accounting educators as they develop classroom instruction and administrators as they contemplate an appropriate emphasis on data modeling in the accounting curriculum.

INTRODUCTION

McCarthy (2003) described the basic principles of the Resource-Event-Agent (REA) framework for data modeling and its application to accounting information systems courses. McCarthy points out that "REA modeling is used in a variety of AIS courses and featured in a variety of AIS textbooks, both in the United States and internationally," and it is beginning to be implemented in introductory accounting courses. The REA framework is also being considered as an e-commerce transaction standard (David et al. 2002). This study examines the effectiveness of the REA framework in promoting improved data modeling performance by accounting undergraduates. Specifically, this research tests the capacity of a single, brief exposure to the REA framework to create lasting improvements in students' ability to identify the entities necessary to create database tables for accounting systems.

Romney and Steinbart (2003) define data modeling as the process of defining a database so that it faithfully represents all key components of an organization's environment. As these authors point out, the objective is to explicitly capture and store data about every business activity that the organization wishes to plan, control, or evaluate. This is precisely why data modeling needs to be a key element of an accounting systems curriculum and is a requisite skill for information technology auditors, risk managers, and accounting system designers and consultants. In addition, basic knowledge of database concepts is becoming essential for all assurance providers because sampling, data extraction, and business process redesign increasingly involve interaction with complex database systems.

Prior research suggests that database models based upon the Resource-Event-Agent (REA) framework more faithfully represent business processes and transaction flows than more traditional debit-credit models of accounting systems (McCarthy 1982; Dunn and McCarthy 1997). Empirical evidence also indicates that students perceive REA models to be more representative of business processes than debit-credit accounting models (Dunn and Grabski 2000), and McCarthy (2003) proposed designing AIS courses around the REA framework. The extant research has not, however, empirically investigated whether classroom instruction in the REA framework actually improves data modeling performance.

The current study employs theories of knowledge structure acquisition and theories of matching task structures to knowledge structures to experimentally investigate the potential benefits of a single exposure to the REA model. Examination of the effects of knowledge of the REA framework on data modeling ability is important to both education and practice. If REA knowledge can be quickly imparted to students and this knowledge significantly improves data modeling ability, then REA modeling should be viewed as a critical component of accounting systems courses. Similarly, the REA framework should be employed in accounting practice if the benefits of improved data modeling skills outweigh the cost of training.

The remainder of the paper describes the relevant literature and develops the hypotheses. Next, we identify the methodology we used for our study, followed by a discussion of the results. The final section includes discussion and conclusions.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Data Modeling

For more than five hundred years, accountants have recorded transactions using the double-entry bookkeeping method. When this method was first developed, it was expensive to gather and store information (Perry and Schneider 2001). However, due to powerful computers and associated technologies, we can now collect, store, and analyze vast amounts of information quickly and efficiently. This increased capacity and speed, combined with managers' increasing demands for qualitative and quantitative information for decision making, has motivated most firms to move to database accounting systems.

Some researchers have argued that accountants should change their understanding of AIS from a financial and transaction analysis to a focus on the economics of business operations, strategic management support, and decision requirements at all managerial levels (e.g., Lainhart 2000; Brecht and Martin 1996; Borthick 1996). Indeed, many accounting information systems (AIS) instructors now use a database approach to accounting systems in their courses to properly prepare accounting students for this environment (McCarthy 2003; Geerts and Waddington 2000).

When companies design a database, data modeling occurs during the requirements analysis stage and the design stage (Romney and Steinbart 2003). Accountants and technology workers typically use Entity-Relationship (ER) diagrams to develop data models. ER diagrams can be used to depict the contents of a database, graphically model an organization, document and understand existing databases, and to reengineer business processes. ER diagrams include many different kinds of entities and relationships among those entities. The REA framework provides a method for organization and critically analyzing ER diagrams. The REA framework provides guidance for database design by identifying which entities should be included in the AIS database and by identifying how to structure relations among the entities in that database. Entities include the economic *Resources* the organization acquires and uses; the economic *Events* in which the organization engages; and the economic *Agents* who participate in the events.

Knowledge Acquisition

Schema theory explains how information in long-term memory is organized and stored. While a number of definitions for schemata exist, Anderson (1985) defines them simply as organized knowledge of the world, and Sweller (1993) defines them as constructs that organize knowledge in the manner in which it will be used. Compelling evidence of schema usage in higher level intellectual activities include Chase and Simon's (1973) discovery that expert chess players have and use schematic knowledge of realistic board configurations, but they do not have such schemata for improbable or impossible board configurations. Similar studies in physics find that experts have problem-solving schemata that allow them to categorize problems according to their solution mode, while novices categorize such problems by surface features (Chi, Glaser, and Rees 1982). Schemata are a primary source of problem-solving skill (Sweller 1993), and the REA framework represents a useful organization of business modeling knowledge.

Historically, researchers believed that schemata were created only from long-term and repeated exposures to concepts. Similarity-based learning theories proposed that learners needed exposure to many examples of a concept before they could integrate the information needed to form lasting knowledge structures (see e.g., Schank and Abelson 1977; Van Dijk and Kintsch 1983). As a result, imparting new knowledge structures to students was thought to require extensive training and practice, often at high costs.

Recent research in learning psychology and expert system development has revealed, however, that new schemata can be acquired from single exposures to examples of a schema (see e.g., Mitchell et al. 1986; Ahn et al. 1992). When participants have sufficient prior knowledge, they are able to create new schemata from only one exposure to a new concept by drawing upon their existing, complex knowledge structures. We propose that participants who have complex, existing knowledge structures for accounting transaction systems can acquire a simple schema of the REA framework from one brief exposure to the REA framework.

Value of the REA Framework

McCarthy (1982) and Dunn and McCarthy (1997) argued that REA accounting models are more semantically expressive than debit-credit accounting models. That is, they theorized that REA models more accurately represent underlying business processes and transaction flows than debit-credit accounting models. Dunn and Grabski (2000) experimentally tested this proposition by evaluating users' perceptions of the expressiveness of debit-credit and REA-framework models of accounting systems. They found that student users perceive REA models to be more helpful than debit-credit models.

A beneficial and necessary extension of the existing REA research is the examination of whether the REA framework enhances accountants' and students' abilities to model business processes. Further, it is constructive to examine the benefits of the REA framework to tasks of varying complexity. Studies have demonstrated that mismatches between users' knowledge organization and the underlying structure of the task can lead to performance deficits (e.g., Ricchiute 1992; Pei and Reneau 1990). Complex modeling tasks that require the generation of many entities and complex relationships may require a modeling framework (i.e., more than just knowledge of the ER diagram techniques).

The present study examines whether data modelers that have acquired knowledge of the REA framework develop more comprehensive and accurate data models than participants who have no exposure to the REA framework. We expect the REA framework to be valuable when modeling complex business processes because students cannot make up for a lack of appropriate knowledge structures with general ability or effort in complex tasks (Bonner and Walker 1994; Libby and Tan 1994). The effects of the REA framework on low complexity tasks are less certain. We suggest that accounting students can acquire an REA schema from a single, brief exposure to REA concepts because the students have a base of rich domain-specific knowledge related to the accounting model and transaction flows. This leads to the first hypothesis.

Hypothesis 1: For complex modeling tasks, students exposed to the REA framework will identify entities more accurately compared to students not exposed to the REA framework.

In less complex tasks, mismatches between knowledge organization and task structure will be less detrimental to modeling performance. In simple modeling tasks, participants can often overcome task/knowledge organization mismatches with general ability or increased effort (Bonner and Walker 1994; Libby and Tan 1994).

Hypothesis 2: Exposure to the REA framework will provide less benefit to students performing simple modeling tasks than to students performing more complex tasks.

RESEARCH METHOD

Participants

The 62 students who participated in this study were junior and senior level accounting students enrolled in an AIS course at a large university. To motivate performance, participants received up to 10 extra credit points (equivalent to one letter grade on the final exam) based on task performance. The extra credit was offered to insure that participants input significant effort to the modeling task.

Experimental Design

The design was a quasi-experiment. Two sections of an Accounting Information Systems course were offered over the course of one semester. Each course section was randomly assigned to a treatment condition. As a result, all student participants in a section were assigned to the same treatment. Participants in the first treatment condition received no instruction on the Resource-Event-Agent (REA) framework. Participants in the second treatment received a single brief lecture (a one-page, written script) explaining the basics of the REA modeling framework. None of the students had access to textbook materials that described the REA framework. The lecture and script provided participants with an REA-based framework for analyzing business processes and developing ER diagrams.

The same instructor taught all sections and performed the scripted lecture. While the instruction was limited to a single exposure to the REA model, this was the intended purpose of the experiment. That is, can a single example of the REA model create a schema and improve task performance? If very limited instruction in REA modeling techniques can significantly improve students' abilities to develop conceptual models, then even minimal implementation in accounting courses could prove very beneficial.

The test phase was administered during class as a written assignment. Two days after receiving instruction on the REA framework (or no instruction), participants completed a low-complexity conceptual modeling problem and a high-complexity conceptual modeling problem. Participants were asked to draw ER diagrams for both the simple and complex scenario. No mention of the REA framework was made in the instructions because half of the participants had never been exposed to the model, and we did not wish to force students to apply the REA framework. Rather, we wanted to determine whether exposure to the REA framework would improve modeling performance and ability to create ER diagrams.

Students' ER diagrams from both the low and high difficulty tasks were scored according to the following key:[1] Missing a Required Entity (-2) and Inappropriate Entity (-1). We emphasized the identification of entities because this a primary benefit of the REA framework (McCarthy 2003). Romney and Steinbart (2003) indicate that the purpose of data modeling is to capture and store data about every business activity that the organization wishes to plan, control, or evaluate. These business activities and associated information are entities. Further, the basic REA model described in the scripted lecture did not discuss modeling cardinalities. The instruments were coded by a graduate student who was unaware of the treatment conditions. Instruments were re-scored by one of the authors, with agreement of 88%. All conflicts were resolved through discussion between the two coders to arrive at a final score. Scores from the ER diagrams were used as dependent variables in analyses of the effects of exposure to the REA framework on data modeling performance.

All participants received instruction on the principles of Entity Relationship (ER) diagramming before the experiment was administered. Students were taught the information engineering method of ER modeling. The ER instruction was provided in the AIS course by the same instructor who gave the REA modeling lecture. All students completed in-class ER modeling examples during class time and a quiz covering the basic concepts of ER diagrams. ER modeling does not require knowledge of the REA framework and can be fully accomplished without any instruction in the REA framework. Further, the REA framework can be applied when creating ER models using any of the popular ER modeling tools such as IDEF1X, information engineering, or the expanded ER model.

Prior research has demonstrated that individual differences can influence conceptual modeling performance. Dunn and Grabski (1998) found that field independent participants perform better on conceptual data modeling tasks than field dependents. To control for field dependence/independence in our study, all participants completed the Group Embedded Figures Test (GEFT) (Witkin et al. 1971). The GEFT score was included as a covariate in the statistical analyses. Accounting grade point average (GPA) was also included as a covariate to control for differences in individual accounting ability.[2] Given that the design was a quasi-experiment, it was important to measure individual ability to insure that individual differences across class sections did not drive the results. Extensive research indicates that individual ability can influence performance, and GPA has been found to be one of the strongest predictors of success in accounting coursework (Hill 1998; Danko et al. 1992; Park and Kerr 1990; Borg et al. 1989).

RESULTS

Entity Identification Performance

Table 1 presents demographic data (Panel A) and descriptive statistics of the number of errors made on the low difficulty and high difficulty ER diagramming problems for all participants (Panel B). No significant differences in age, GPA, or GEFT score were noted across sections. For both the low and high difficulty problem, participants made fewer errors in their data models when they had been exposed to the REA framework.

Table 1: Demographics And Performance Scores

Panel A – Demographic Data

Treatment	N	Age	GPA	Group Embedded Figures Score
No REA Lecture	29	20.35 (1.08)	2.56 (0.54)	54.38 (10.61)
REA Lecture	32	20.22 (.71)	2.51 (0.42)	48.66 (10.89)
Overall	61	20.28 (0.90)	2.53 (0.48)	51.38 (11.05)

cells contain means and standard deviations in ()

Panel B - Number of Errors on Data Modeling Test by Treatment and Problem Complexity

Treatments	Problem Complexity	N	Mean Errors	SD
No REA Lecture	Low	29	2.69	1.11
	High	29	11.17	3.07
REA Lecture	Low	32	2.25	1.16
	High	32	6.19	1.86

The first hypothesis posited that in high-difficulty modeling tasks, participants with an understanding of the REA framework would develop more accurate and thorough data models than participants without exposure to the REA framework. Table 2 presents the results of an ANCOVA model with the score on the high-difficulty modeling problem as the dependent variable. The manipulated independent variable is the treatment (REA exposure or no REA exposure) and covariates are included for GPA and GEFT score. The treatment variable is statistically significant (p<.001), indicating that students perform better on data modeling tasks when they have been exposed to the REA model. The first hypothesis is supported. The result holds after controlling for individual ability and field dependence/independence. Consistent with prior research, field independents performed better on the conceptual modeling task than field dependents. In addition, field independents benefited more from the REA instruction than field dependents.

Table 2: ANCOVA for Score on High Complexity Modeling Problem

Source	Sum of Squares	df	Mean Square	F	Sig.
Treatment[a]	388.35	1	388.35	85.83	0.000
GPA[b]	0.30	1	0.3	0.06	0.798
GEFT Score[c]	77.94	1	77.94	17.23	0.000
Treatment*GEFT	39.09	1	39.09	8.64	0.005
Error	253.37	56	5		
Total	5216.00	61			

R square = ..662

[a] Half of the participants received a brief lecture on REA modeling and half did not receive the REA lecture.
[b] GPA is the participant's accounting grade point average. GPA controls for individual ability.
[c] The GEFT score is a categorical variable derived from a median split of the score from the Group Embedded Figures Test, and it controls for field dependence/independence.

The second hypothesis proposed that exposure to the REA framework would not improve data modeling performance in simple modeling tasks as much as in complex modeling tasks. To begin analysis of hypothesis two, a second ANCOVA model is developed with the score on the low-complexity modeling task as the independent variable. This model is presented in Table 3. In this model, the treatment variable is not statistically significant at conventional levels (p<.108). The explanatory power of the model is also reduced relative to the model for the high-difficulty modeling problem. It appears that knowledge of the REA model is less beneficial in simple tasks.

Table 3: ANCOVA for Score on Low Complexity Modeling Problem

Source	Sum of Squares	df	Mean Square	F	Sig.
Treatment[a]	3.19	1	3.19	2.66	0.108
GPA[b]	2.93	1	2.93	2.44	0.124
GEFT Score[c]	4.86	1	4.86	4.06	0.049
Treatment*GEFT	3.03	1	3.03	2.53	0.117
Error	67.10	56	1.20		
Total	448.00	61			

R square = .152

[a] Half of the participants received a brief lecture on REA modeling and half did not receive the REA lecture.
[b] GPA is the participant's accounting grade point average. GPA controls for individual ability.
[c] The GEFT score is a categorical variable derived from a median split of the score from the Group Embedded Figures Test, and it controls for field dependence/independence.

To directly test the second hypothesis, we employ a repeated measures model (see Table 4). The within-participants variable is problem difficulty and the between-participants variables are treatment, GPA, and GEFT score. The complexity variable is statistically significant (p<.001), which indicates that students perform worse on the more complex modeling task. More importantly, the interaction of problem difficulty and treatment is statistically significant (p<.001). When participants are exposed to the REA framework, their modeling performance improves more when the modeling task is more complex, relative to tasks that are less complex. These findings support our second hypothesis.

Table 4: Repeated Measures Model – Performance on the Data Modeling Test

Source	Sum of Squares	df	Mean Square	F	Sig.
Within Subjects Effects					
Problem Complexity[a]	84.83	1	84.83	23.79	0.000
Difficulty * Treatment	189.61	1	189.61	53.18	0.000
Between Subjects Effects					
Treatment[b]	240.29	1	240.29	74.15	0.000
GPA[c]	1.45	1	1.45	0.45	0.040
GEFT Score[d]	14.32	1	14.32	32.16	0.000

[a] The ER modeling problems were either low or high complexity.
[a] Half of the participants received a brief lecture on REA modeling and half did not receive the REA lecture.
[c] GPA is the participant's accounting grade point average. GPA controls for individual ability.
[d] The GEFT score is the total score from the Group Embedded Figures Test, and it controls for field dependence/independence.

CONCLUSIONS

The REA framework has been demonstrated to more faithfully represent business processes than debit-credit accounting models, which indicates that teaching the REA framework could help students understand a variety of essential database, accounting, and auditing concepts. More and more firms are adopting enterprise resource planning (ERP) systems that completely integrate an organization's business information processing systems and all related data. Modern accountants and auditors must understand complex business processes and automated information systems. Data modeling proficiency is one essential component of these new skill sets.

The results from a classroom experiment indicate that, after controlling for individual differences that may affect data modeling ability, a single exposure to the REA framework significantly improves students' data modeling performance when the modeling task is complex. The results are important because they indicate that certain complex knowledge structures can be imparted to students at very low cost, and these knowledge structures improve task performance. The results also provide useful guidance for database instruction and training. Even if AIS instructors do not believe they have a significant amount of class time to devote to data modeling, a limited presentation of the REA framework has the potential to improve students' knowledge of business processes, data modeling skills, and ability to describe complex accounting systems.

Constant advances in technology have enabled an increasingly connected business world that has become progressively more complex. Such a market place demands that entry-level accountants understand the financial aspects of the company as well as the myriad of business processes that occur within the organization. Our results suggest that AIS educators have an opportunity to improve students' knowledge of business processes and performance on data modeling tasks with limited instructional resources or effort. Further, limited instruction improves performance on a highly complex task.

The results must be considered in light of the limitations of the study. The design was a quasi-experiment, where each participant was not randomly assigned to the treatment condition. As a result, differences in class sections could influence the results. We controlled for individual ability and field dependence (an individual difference known to influence modeling performance), and we analyzed demographic data for differences across course sections. While we detected no significant individual differences across sections and implemented covariate control variables, there could be unmeasured variables that would affect the two course sections. Finally, there are multiple potential measures of modeling performance. We developed measure of entity identification and also considered alternative scoring approaches. It is possible that other modeling performance measures such as the creation of relationships and assignment of cardinalities to relationships could yield different results.

FOOTNOTES

1. Alternative scoring methods (such as only counting missing entities) produce similar results.
2. The grade point average (GPA) was the actual GPA, not self-reported GPA.

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