JOURNAL OF INFORMATION SYSTEMS
Vol. 19, No. 2
Fall 2005
pp. 57–77

The REA Pattern, Knowledge Structures, and Conceptual Modeling Performance

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ABSTRACT: Most database textbooks on conceptual modeling do not cover domain-specific patterns. The texts emphasize notation, apparently assuming that notation enables individuals to correctly model domain-specific knowledge acquired from experience. However, the domain knowledge acquired may not aid in the construction of conceptual models if it is not structured to support conceptual modeling. This study uses the Resources Events Agents (REA) pattern as an example of a domain-specific pattern that can be encoded as a knowledge structure for conceptual modeling of accounting information systems (AIS), and tests its effects on the accuracy of conceptual modeling in a familiar business setting. Fifty-three undergraduate and forty-six graduate students completed recall tasks designed to measure REA knowledge structure. The accuracy of participants' conceptual models was positively related to REA knowledge structure. Results suggest it is insufficient to know only conceptual modeling notation because structured knowledge of domain-specific patterns reduces design errors.

Keywords: domain-specific training; knowledge structure; conceptual database design; data modeling pattern; REA.

Data Availability: Contact the author.

I. INTRODUCTION

> Experienced designers evidently know something inexperienced ones don't. What is it? One thing expert designers know *not* to do is solve every problem from first principles. Rather, they reuse solutions that have worked for them in the past. When they find a good solution, they use it again and again. Such experience is part of what makes them experts ... A designer who is familiar with such patterns can apply them immediately to design problems without having to rediscover them. (Gamma et al. 1995, 1)

Interest is growing in conceptual modeling research. Design errors are expensive and detecting them early can save enormous expense. Undetected conceptual model design errors are implemented into the database. Such errors are estimated to account for 55 to 85 percent of total software errors (Card and Glass 1990). Post-implementation changes to

This paper is based on my dissertation at Michigan State University (which was awarded the 1999 AAA Information Systems Section Outstanding Dissertation Award). I would like to thank the members of my dissertation committee, Bill McCarthy (Chair), Frank Boster, Sev Grabski, and Joan Luft, for their guidance and support. I also thank the following for their helpful comments: Cheryl Dunn, Cindy Durtschi, Richard Dusenbury, Bud Fennema, Malcolm McLelland, Jane Reimers, Eugene Wallingford, Ron Weber, and workshop participants at Arizona State University, Florida State University (accounting, MIS, and psychology departments), Michigan State University, North Carolina State University, and Virginia Polytechnic Institute and State University.

correct errors typically absorb 40 to 50 percent of the total project cost (Boehm 1989). Even if errors are detected before implementation, they increase the overall cost of the system; costs rise exponentially during the time it takes to discover an error (Moody 1998). Wand and Weber (2002) recently outlined an ambitious research agenda for conceptual modeling that advocates, in part, the study of training and education factors to improve individuals' conceptual modeling performance. The current study seeks to determine whether conceptual modeling performance can be enhanced if designers know domain-specific patterns of objects and the relationships between objects. At issue is whether training and education programs should incorporate teaching of domain-specific patterns.

Although a precise definition of *pattern* in the context of systems analysis and design is elusive (Fowler 1997; Hay 1996; Gamma et al. 1995), common opinion recognizes that a pattern is a *generalizable reusable solution to a design problem.* In the current study, pattern is defined operationally as McCarthy's (1982) pattern of resources, events, and agents (REA), and related duality, stock/flow, and control relationships. Although REA is independent of any specific conceptual modeling notations, it is commonly illustrated using the entity-relationship (E-R) conceptual model (Chen 1976; Batini et al. 1992). In the E-R model, sets of objects are represented as entities, and sets of associations between objects are represented as relationships. Entities and relationships can be combined in various ways depending on domain and the modeler's interpretation of the domain. As one gains domain experience, patterns of entities and relationships emerge. In the accounting information systems domain, McCarthy (1982) used this form of pattern recognition to derive the REA pattern. Other domains, of course, have their own patterns (Coad et al. 1995; Fowler 1997; Hay 1996; Gamma et al. 1995).

In principle, conceptual modeling can be performed *without* domain-specific patterns such as REA. Consequently, it is unclear whether such knowledge contributes to the accuracy of conceptual models. Almost all database texts covering conceptual modeling (see e.g., Rob and Coronel 2004; Kroenke 2004; Watson 2002; Batini et al. 1992) *do not* emphasize domain-specific patterns (but see Dunn et al. 2005 for a notable exception). In these texts, conceptual model notation is considered a general tool that must be mastered independent of domain. However, important implicit assumptions underlie such thinking: (1) individuals acquire domain knowledge from work experience (including, e.g., day-to-day observation, reading information requirements, reviewing conceptual models of others, interviewing users), and, (2) conceptual modeling notation enables the translation of domain knowledge into a conceptual model. If these assumptions are true, then knowledge of domain-specific patterns such as REA should not influence conceptual modeling performance. However, the domain knowledge people obtain from observation and well-written descriptions does not necessarily have the abstract structure that is needed for effective conceptual modeling. So we need a better understanding of the type of domain knowledge that improves conceptual modeling performance.

To determine how knowledge of domain-specific patterns affects performance, the experiment reported herein measures REA knowledge structure and tests its consequences for conceptual modeling. Knowledge structure is understood as the organization of knowledge in memory. The duality, stock/flow, and control relationships in REA allow for knowledge of resources, events, and agents to be related in a knowledge structure. Prior research suggests that knowledge structures develop with domain-specific experience (see e.g., Chase and Simon 1973; Chi et al. 1982). To measure REA knowledge structure 46 graduate and 53 undergraduate students, at two respective levels of domain-specific experience derived from training, completed a free recall experiment involving two E-R diagrams, one structured according to REA and the other not. Consistent with prior psychology research, those with more domain-specific REA training recalled more information (entities, relationships, cardinalities) than those with less domain-specific REA training when the E-R diagram was structured according to the REA pattern. Recall performance was approximately equal across groups when the E-R diagram was not structured according to the REA pattern. Although this shows the relationship between domain-specific experience and REA knowledge structure, a question remained as to whether REA knowledge structure is associated with conceptual modeling performance. Therefore, participants completed the second phase of the study briefly described next.

Participants completed an E-R model for the revenue and acquisition cycles of a business that rents videos and sells candy. Retail businesses in general, and video rental and candy sales in particular, were expected to be a familiar domain for participants. In addition to whatever experience-based, domain-specific knowledge they had, participants received a business description narrative that provided all the information participants needed to construct a correct conceptual model. Furthermore, all participants knew E-R modeling notation. In essence, this setting allowed for evaluation of the implicit assumptions above.

Participants' models were scored to measure conceptual modeling performance accuracy. This measure was regressed on the REA knowledge structure measure. Results indicated that knowledge of a domain-specific pattern, REA, was associated with fewer design errors. This shows that the domain-specific knowledge acquired from experience (e.g., by renting videos and studying written descriptions of the business) is insufficient, in combination with training in conceptual modeling notation, to produce effective conceptual modeling performance. The significance of the REA pattern is that it provides an abstract structure that helps people identify what entities to look for and what relationships should exist.

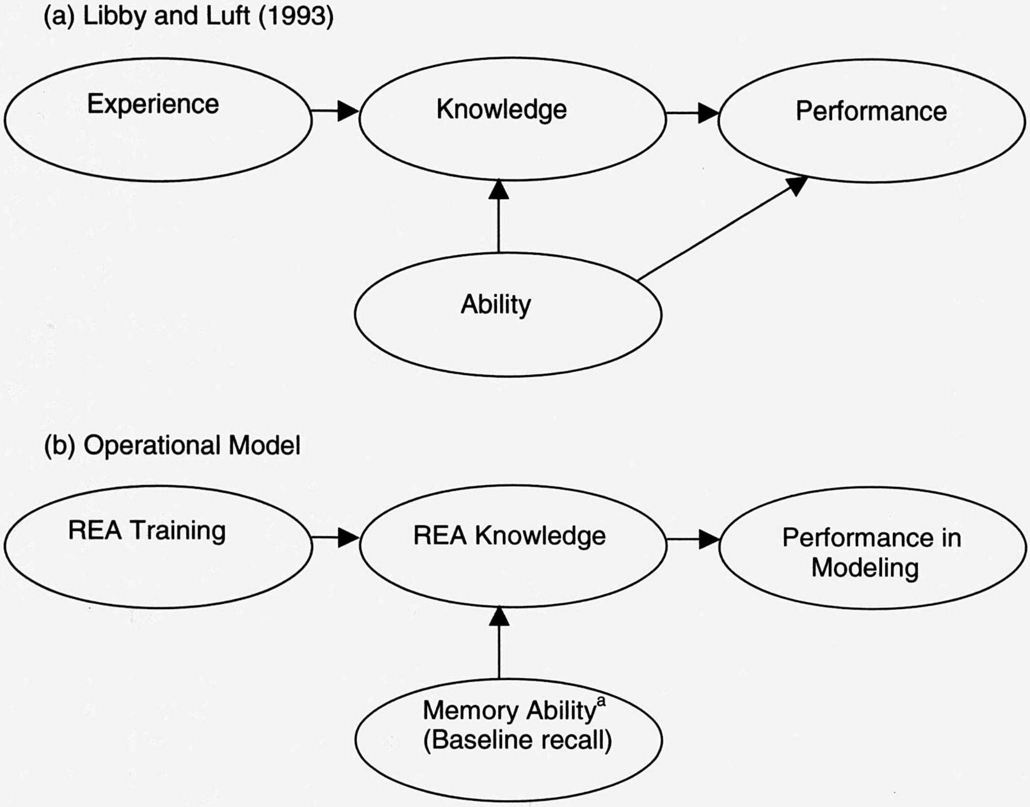
II. RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

This study follows Libby and Luft's (1993) antecedents and consequences of knowledge research model (see Figure 1a). Performance is a function of knowledge and ability, and knowledge is a function of experience and ability. Motivation and environment are also a part of Libby and Luft's (1993) model, but this study assumes these factors to be constant. Figure 1b shows this study's operationalized model. While the primary objective of this study is to examine the relationship between REA knowledge and conceptual modeling performance, it was necessary to first measure the structure of REA knowledge. The theoretical basis for measuring the REA knowledge structure is discussed next.

Experience/Knowledge Structure Relationship

Considerable accounting research examines the roles of knowledge and knowledge structures (Smith and Kida 1991; Bedard and Chi 1993; Libby and Luft 1993; Libby 1995; Nelson et al. 1995). A general finding is that domain-specific experience is associated with the development of knowledge structures (see e.g., Chase and Simon 1973; Chi et al. 1982; Ericsson and Lehmann 1996; Butt 1988; Tubbs 1992). Weber (1980) shows that the structure of information system controls knowledge is associated with electronic data processing (EDP) audit experience. Rose and Wolfe (2000) define learning as the acquisition of schemata (i.e., knowledge structures). Since learning can occur on the job or via training,

FIGURE 1
Antecedents and Consequences of Knowledge Model (Libby and Luft 1993) and Operational Model



[a] Memory ability is an antecedent to knowledge and knowledge acquisition. However, memory ability as used in this research is a baseline of what can be recalled when a diagram is not structured according to REA. This baseline is then compared to recall when a diagram is structured according to REA.

domain-specific knowledge structures can likewise develop on the job or via training. Research also indicates that experts' knowledge structures have more knowledge, more knowledge of relationships, and more abstract knowledge (Chi et al. 1982).[1] Knowledge structures are advantageous because they facilitate the recall of information, and they allow the limited capacity of working memory to be exceeded (Miller 1956; Baddeley 1994).

Knowledge structures differ depending on the knowledge represented, and various concepts have been proposed such as scripts (Schank and Abelson 1977), schemata (Rumelhart 1980), and frames (Minsky 1975) to account for knowledge structures. These types of knowledge structures have common characteristics in that they use variables and relationships between variables to encode general knowledge that can be applied to many situations,

[1] The current study examines experience (operationalized as training) instead of expertise (Davis and Solomon 1989). However, the research methods and findings from the expertise literature are relevant to the study of knowledge structure.

and they use values to instantiate variables in a specific situation (Eysenck and Keane 1995, 263). The REA pattern can be encoded as a knowledge structure representing economic agents exchanging resources through related events. The REA variables are resources, events, and agents (see Figure 2a). Duality, stock/flow, and control describe relationships between the variables. These associations describe the causal or purposeful nature of economic exchange. Values can fill the variables in revenue, acquisition, and conversion processes. For example, in the revenue process depicted in Figure 2b, sale is a value that instantiates a "give-event" variable, and cash receipt is a value that instantiates a "take-event" variable.

Knowledge structures must be inferred using cognitive psychology tasks (e.g., free recall).[2] Prior research indicates that domain-specific experience is associated with the development of knowledge structures and that knowledge structures facilitate chunking. Therefore, if individuals with more training in REA-patterned conceptual modeling form an REA knowledge structure, they should be able to recall more information than individuals with less training in REA (who are in earlier stages of knowledge structure development) when diagrams are based on the REA pattern. However, diagrams that do not include the REA pattern will not match the more-trained-in-REA individuals' REA knowledge structures, and they will not be able to recall more information than less-trained-in-REA individuals will. Therefore, the following interaction is hypothesized:

> **H1:** Participants receiving more REA training will recall more information than participants receiving less REA training, only in the domain with an REA pattern.

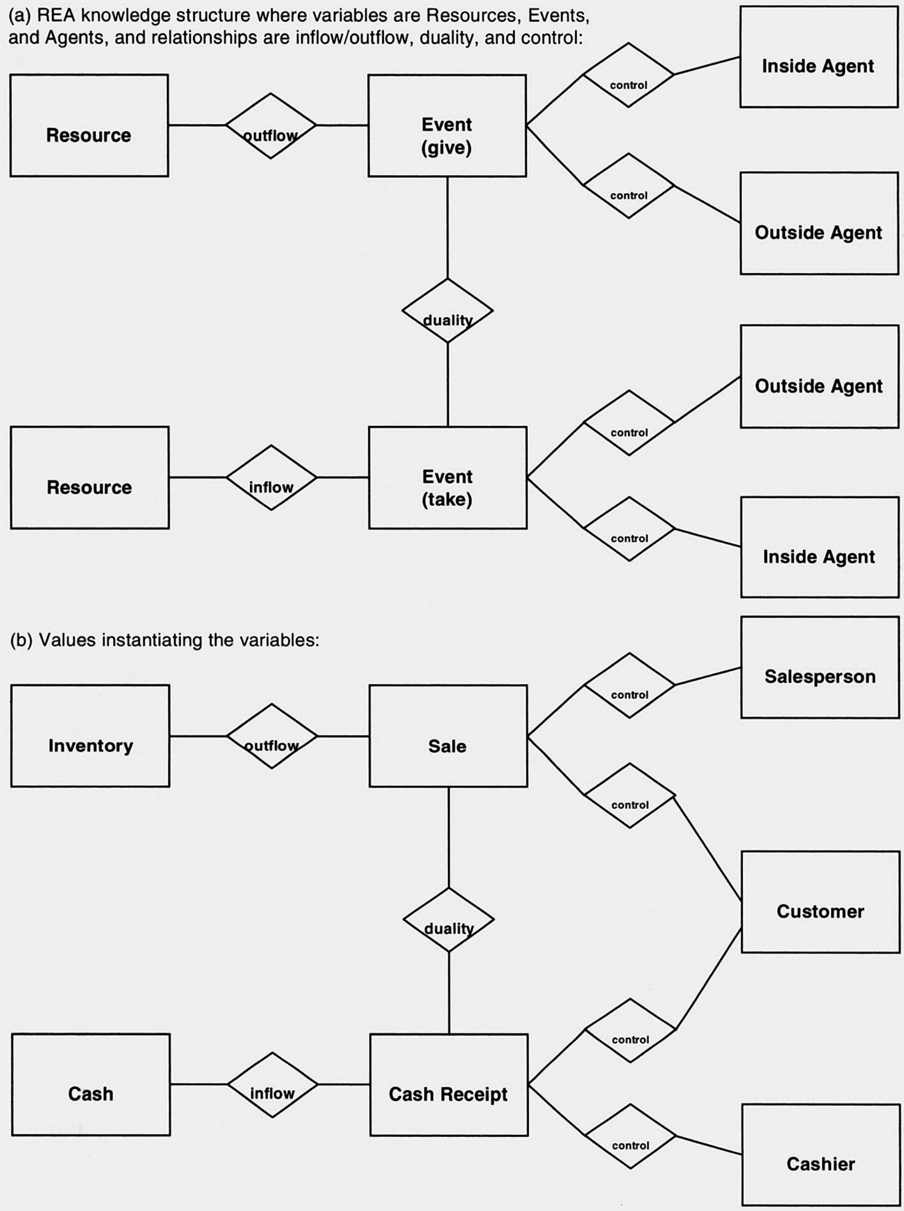
Support for this hypothesis will show that (1) REA training affects knowledge structure, and, more importantly, (2) the measured knowledge structure is not due to differences in innate memory ability. While past research indicates that support for the hypothesis is likely, it is unclear how much training individuals need to develop an REA knowledge structure. Perhaps those less-trained-in-REA have a well-developed knowledge structure and only a main effect will obtain. Regardless, because no measure of REA knowledge structure exists, it is necessary to obtain such a measure to examine the relationship between knowledge structure and conceptual modeling performance.

Knowledge/Performance Relationship

How does domain knowledge relate to performance? Many studies have used experience as a proxy for knowledge, showing that there is a positive relationship between experience and performance. However, Libby (1995, 194) suggests that, rather than using experience as a surrogate for knowledge, researchers could use direct measures of knowledge as independent variables in studies that aim to explain performance. Only a limited

[2] The chess studies of de Groot (1965, 1966; also see Chase and Simon 1973) are a clever example of how free recall can be used to infer knowledge structures. Chess players with more or less expertise were shown either "normal" board positions taken from real games or "random" board positions. The board positions were removed, and participants were asked to recall the positions. The approximate recall accuracy of the experts for normal board positions was more than double the accuracy of those with less expertise. For recall of the random board positions, however, this difference disappeared, and performance was similar across expertise levels. The chess experts did not have superior memories, but, instead, had apparently developed specific knowledge structures for certain board patterns they had experienced. The knowledge structures allowed the experts to chunk "normal" game board pieces together in working memory and surpass the normal working memory limitations.

FIGURE 2
Example of General REA Pattern Encoded as a Knowledge Structure



number of accounting studies have tested the knowledge-performance relationship directly using knowledge as an independent variable (see e.g., Libby and Frederick 1990; Bonner and Lewis 1990; Heiman 1990). The key to using a direct measure of knowledge is identifying the specific knowledge that is relevant for task performance (Libby 1995; Libby and Luft 1993).

To identify the applicable knowledge, the conceptual modeling task must be considered. In this study, the task involves entity-relationship modeling of economic exchanges. Therefore, successful task completion requires two areas of knowledge: E-R modeling knowledge and REA knowledge.

For each of these areas of knowledge, it is important to distinguish between knowledge *content* and *structure*. *Knowledge content* refers to the information stored in memory; *knowledge structure* refers to the organization (e.g., hierarchical, temporal, causal) that is placed on the memory content. For example, knowledge content includes knowing the elements of REA or the E-R model. REA knowledge structure is imposed on the knowledge content and assumed to be organized according to the relationships and variables illustrated in Figure 2a.

To further elaborate, E-R modeling knowledge relates to content. Individuals with training know the constructs of the E-R model, such as what an entity is, what a relationship is, what a primary key is, what cardinalities mean, etc. Likewise, some REA knowledge is content; for example, that a sale is an event, and that inventory is a resource. However, as mentioned above, some REA knowledge is structure, e.g., knowledge that sale and inventory should be related because of the stock/flow relationship between the event (sale) and the resource (inventory).

Another type of knowledge that could be applicable to performance in a conceptual modeling task is *attribute aggregation knowledge* (knowledge of how attributes aggregate to entities). To the extent that designers use a "bottom-up" strategy starting with attributes to identify entities, attribute aggregation knowledge may affect design performance. For example, Batini et al. (1992, 64) describe a bottom-up design where the designer starts with the list of attributes *name*, *sex*, *age*, *city*, and *state*, and identifies the resulting entities *person* and *place*. The use of the REA pattern would imply a "top-down" strategy where the entities and relationships would be identified and attributes would be subsequently assigned. Batini et al. (1992) suggest that designers can mix strategies. It is assumed that the REA knowledge structure measure proxies for a top-down strategy.

To summarize, there are multiple dimensions of relevant knowledge that might influence conceptual modeling performance—content, structure, and attribute aggregation (which is a form of knowledge structure separate from REA knowledge structure). Knowledge content and performance are positively associated. Furthermore, due to the possible effect of attribute aggregation on performance, researchers should attempt to measure and statistically control for the approach. That leaves the fundamental question of this study: Is REA knowledge structure related to an incremental performance effect because conceptual modeling can be performed without knowledge of domain-specific patterns? The implicit assumption is that knowledge content is sufficient for effective conceptual modeling.

The domain knowledge acquired from daily-life observation and well-written information requirements does not necessarily have the abstract structure that is necessary for effective conceptual modeling. Therefore, individuals without the abstract structure will either omit relevant information or structure it ineffectively. REA solves this problem by imposing a domain-specific pattern that, when encoded as a knowledge structure, helps individuals identify what entities to look for and what relationships they should have. Additionally, REA knowledge structures allow individuals to hold more information in working memory during conceptual model construction. This is significant because information left out of working memory will be left out of, or potentially misplaced in, the conceptual model. For these reasons, REA knowledge structure should be related to conceptual modeling performance. This is formalized in the second hypothesis:

H2: *Ceteris paribus*, conceptual modeling performance will be positively correlated with REA knowledge structure.

Hypotheses 1 and 2 were tested in two phases. In Phase 1, REA knowledge structure was measured by participants' recall performance. In Phase 2, the primary focus of this research, the performance implications of REA knowledge structure were examined by (1) having participants design conceptual models, (2) measuring the accuracy of those models, and (3) regressing the accuracy on the REA knowledge structure measure and other variables that affect performance.

III. PHASE 1: INFERRING REA KNOWLEDGE STRUCTURE

Method

Participants

Fifty-three undergraduate and 46 graduate students with average ages of 21.2 years and 25.1 years respectively completed this study. These participants had experience on two different levels of training using the REA model (i.e., those more and less trained in REA) as discussed below.[3] Responses to a questionnaire indicated that none of the students had on-the-job IS design or relational database work experience.[4] Participants received class credit worth 6 percent of their final grade for completing the experiment.

Participants were recruited near the end of the semester from two accounting courses at a large mid-western university. The first course was a required undergraduate accounting information systems (AIS) course based on REA modeling, and the second course was a graduate database course based on advanced REA modeling that is required for students choosing to specialize in the "systems track" of the Master's of Accountancy program.[5]

Analysis of syllabi and discussions with the graduate course instructor revealed that the extra training acquired in the graduate course related to (1) more practice with REA modeling, (2) more feedback on REA modeling tasks, (3) the use of advanced conceptual modeling techniques (particularly generalization abstractions), and (4) the use of more complex design problems involving partial determinacy diagrams. The undergraduate course concentrated on the basic principles of the REA framework and basic database design techniques using less complex design problems than the graduate course. The E-R model was the chosen conceptual model for both courses. Care was taken in creating the experimental materials to preclude any bias based on concepts that would have been taught to the graduate students but not undergraduates, such as generalization abstractions and partial determinacy diagrams. The conceptual modeling task, discussed later, was of reasonable scope to allow the less-trained-in-REA group to solve it accurately.

Materials

In addition to blank paper and writing implements for participants, Phase 1 included two E-R diagrams, depicted on separate sheets of paper. Two academic experts in REA and

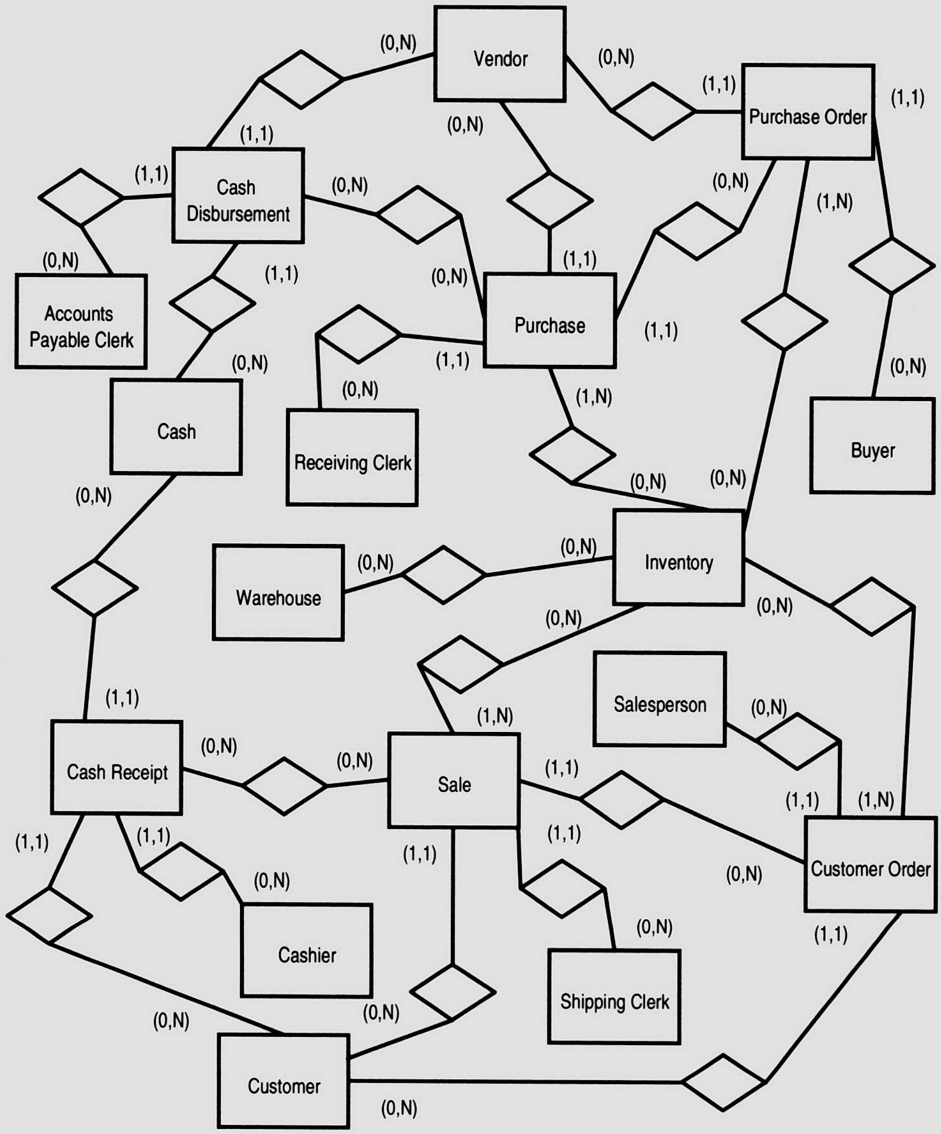
[3] Libby (1995, 180) describes experience as "task-related encounters that provide opportunities for learning." Libby (1995, 180, emphasis in the original) further distinguishes between "*First-hand encounters*, including task completion and reviewing the work of others, receipt of review comments from superiors (process feedback), and outcome feedback," and "*Second-hand encounters*, including discussion of other audits with colleagues, reading formal audit guides, and education and training."

[4] Five of the students had professional work experience related to information systems, or, accounting and auditing.

[5] All students enrolled in the graduate database course had taken the undergraduate AIS course, or its graduate-level equivalent, as a prerequisite. Slightly over half of the graduate students entered graduate school immediately after completing their undergraduate degree in accounting at the same university.

E-R modeling reviewed the diagrams and determined them to be valid representations for the purpose of this study. The first (see Figure 3) diagram depicted revenue and acquisition processes as prescribed by the core REA pattern (see McCarthy 1982), including duality, stock/flow, and control relationships. This diagram extended the core REA pattern to include commitment images and their relationships with internal agents, external agents, resources, and events that fulfill the commitments (see e.g., Geerts and McCarthy 2002;

FIGURE 3
***ER with REA* Diagram for Free Recall (Phase 1 of Experiment)**



Dunn et al. 2005). The second E-R diagram used in Phase 1 (see Figure 4) was developed by rearranging the names of entities and cardinalities while preserving the spatial orientation of the symbols from the first diagram. Therefore, both diagrams had the same spatial orientation of entity and relationship symbols, but one of the diagram's relationships and cardinalities conformed to the principles of the REA model and the other did not. From here on, these two treatments are called *ER with REA* and *ER without REA*.

Procedures

After a brief overview, willing participants provided informed consent. The more-trained-in-REA and less-trained-in-REA participants completed the experiment in separate administrations in a university classroom.

Participants received one of the two diagrams to study for three minutes (consistent with Weber 1996). They then placed the diagram face down and reconstructed it from memory. After ten minutes of recall, these materials were collected, and participants completed an attribute recall task to be described later. Then, the procedures were repeated with the other diagram. The order in which the diagrams were presented was counterbalanced to control for order effects. All materials and procedures were pilot tested and appropriate changes were made.

Dependent Variables and Data Coding

REA knowledge structure is operationalized as the total number of information items recalled from the *ER with REA* diagram; this measure is termed *REA_Recall* in the subsequent analysis.[6] With each individual entity, relationship, and cardinality defined as separate information items, the *ER with REA* diagram included 132 total items.

In addition to *REA_Recall*, a second dependent variable, termed *BASELINE*, is a measure of the number of items participants recalled from the *ER without REA* diagram, which also included 132 total items. *BASELINE* is a measure of memory ability (see Figure 1b).

For both dependent variables, the author coded information items based on the following rules.

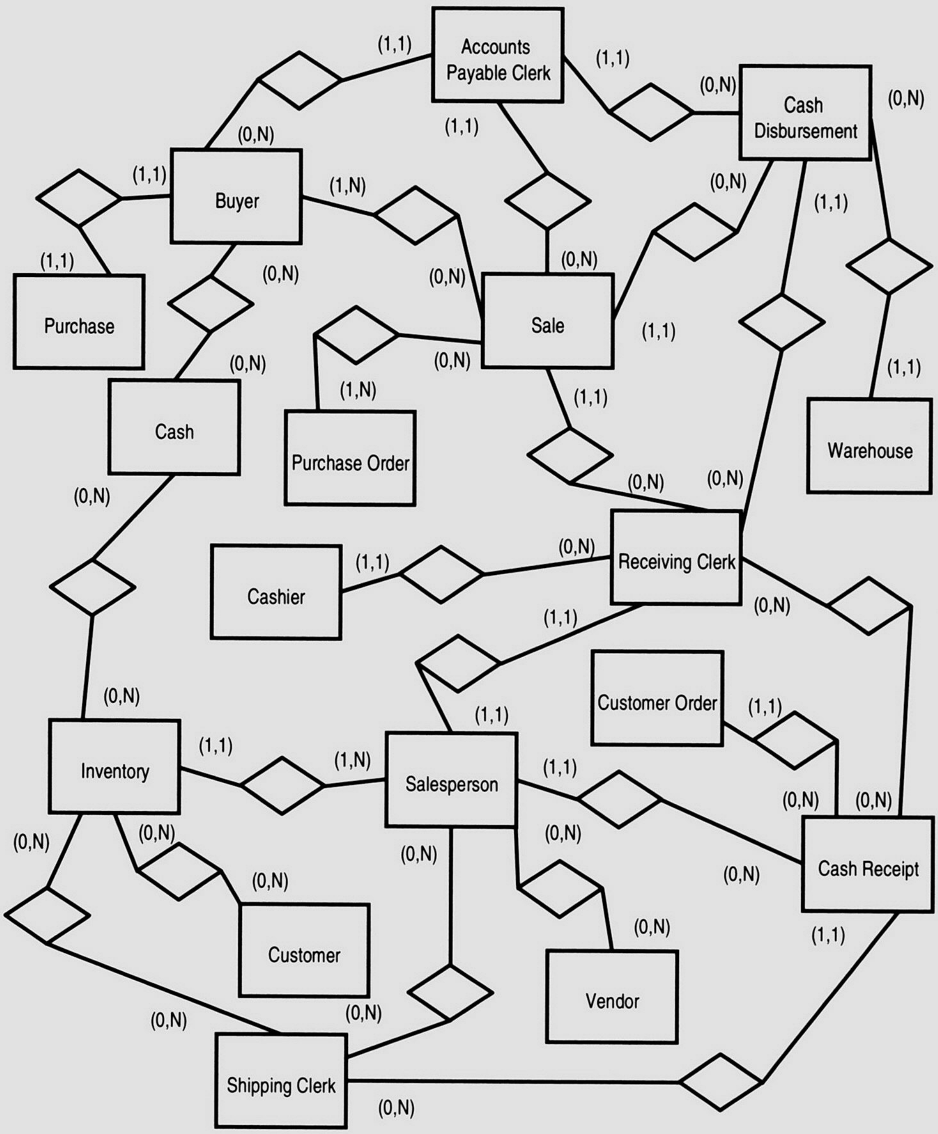
(1) One point was awarded for each entity recalled. An entity includes both the rectangle symbol and a valid entity name.
(2) One point was awarded for each relationship recalled. Relationships were considered valid only if they connected two valid entities; a disconnected diamond symbol or a diamond connected to only one entity was not counted.
(3) Finally, one point was awarded for each minimum or maximum cardinality recalled and assigned to a valid relationship.

As an alternative measure of *REA_Recall*, *REA_Recall2* was derived based on a count of the total number of valid relationships recalled. *REA_Recall2* was used to see if the results were contingent on the measurement of recall.

The author performed all coding. To determine coding reliability, a research assistant who was blind to the research hypotheses randomly selected and coded approximately 33 percent (18 from the undergraduate group and 16 from the graduate group) of the sample. Reliability was evidenced by 100 percent agreement between coders for the *ER without REA* diagram scores and near-perfect agreement (r = 0.9999) for the *ER with REA* diagram scores.[7] All differences were reconciled by discussion.

[6] Prior literature identifies total number of items recalled as an acceptable method for measuring knowledge structure (see e.g., Murphy and Puff 1982).
[7] The Pearson correlation coefficient measures association not agreement.

FIGURE 4
***ER without REA* Diagram for Free Recall (Phase 1 of Experiment)**



Results

Descriptive Statistics

Table 1, Panel A, shows the means and standard deviations of the total number of items recalled for each REA training level and diagram type. For the *ER with REA* diagram, the more-trained-in-REA participants recalled an average of 64.70 information items (49 percent of the total information available), whereas the less-trained-in-REA participants recalled an average of only 30.66 information items (23 percent of the total information

TABLE 1
Descriptive Statistics and ANOVA Models for Total Number of Items Recalled and Total Number of Relationships Recalled

Panel A: Means (Standard Deviations) of the *Total Number of Items* Recalled by REA Training Level and Diagram Type

		Less-trained-in-REA Group (n = 53)	More-trained-in-REA Group (n = 46)
ER with REA Diagram	M	30.66	64.70
	(SD)	(13.91)	(29.79)
ER without REA Diagram	M	20.79	23.70
	(SD)	(6.74)	(13.65)

Panel B: ANOVA Effect of REA Training on the *Total Number of Items* Recalled

Source	df	SS	MS	F	p
Between Subjects					
REA Training	1	16,800.66	16,800.66	48.46	<0.0001
Residual Between	97	33,631.04	361.71		
Within Subjects					
Diagram Type	1	31,860.79	31,860.79	113.94	<0.0001
REA Training × Diagram Type	1	11,933.96	11,933.96	42.68	<0.0001
Residual Within	97	27,123.04	279.62		

Panel C: Means (Standard Deviations) of the *Total Number of Relationships* Recalled by REA Training Level and Diagram Type

		Less-trained-in-REA Group (n = 53)	More-trained-in-REA Group (n = 46)
ER with REA Diagram	M	11.47	16.30
	(SD)	(4.31)	(3.84)
ER without REA Diagram	M	7.32	7.13
	(SD)	(3.65)	(4.34)

Panel D: ANOVA Effect of REA Training on the *Total Number of Relationships* Recalled

Source	df	SS	MS	F	p
Between Subjects					
REA Training	1	265.36	265.36	14.50	<0.0002
Residual Between	97	1,775.01	18.30		
Within Subjects					
Diagram Type	1	2,186.22	2,186.22	152.05	<0.0001
REA Training × Diagram Type	1	310.66	310.66	21.61	<0.0001
Residual Within	97	1,394.70	14.38		

available). For the *ER without REA* diagram, performance between groups was similar. The more-trained-in-REA participants recalled an average of 23.70 information items versus the less-trained-in-REA participants' average of 20.79 items.

Test of Hypothesis 1

Hypothesis 1 predicts that recall will follow this pattern: the more-trained-in-REA participants will recall more information than less-trained-in-REA participants—but only in the environment where information is structured according to the REA pattern. This hypothesis was tested using a mixed design with one between-subjects factor (REA training), and one within-subjects factor (diagram type). The dependent variable was the total recall score (either *REA_Recall* or *BASELINE*). The ANOVA analysis, summarized in Table 1, Panel B, revealed a significant interaction between REA training and diagram type, $F(1, 97) = 42.68$, $p < .0001$. Tests for simple effects revealed that the difference in *ER without REA* diagram recall between the more-trained-in-REA and less-trained-in-REA groups was not statistically significant [$F(1, 97) = 1.87$, $p < .18$], but the more-trained-in-REA group recalled significantly more [$F(1, 97) = 55.33$, $p < .0001$] than the less-trained-in-REA group on the *ER with REA* diagram. These results are consistent with Hypothesis 1.[8]

Table 1, Panels C and D, reveal a similar pattern of means and standard deviations and similar ANOVA results for the alternative recall accuracy measure *REA_Recall2*. Data analysis revealed no statistically significant order effects.

When recalling the *ER with REA* diagram, more-trained-in-REA participants outperformed the less-trained-in-REA participants. The results suggest that the REA pattern can be encoded as a knowledge structure given sufficient training. This study makes an important contribution: evidence of knowledge structure development based on training. However, the significance of this finding will be enhanced if the REA knowledge structure is associated with improved conceptual modeling performance.

IV. PHASE 2: PERFORMANCE IMPLICATIONS OF REA KNOWLEDGE STRUCTURE

Method

Materials

In the conceptual modeling task, participants received a two-page narrative with revenue and acquisition process descriptions, and a list of attributes for a fictitious enterprise (a videotape-rental company) chosen because all participants would be familiar with how video rental stores operate. The task has a large amount of information that must be processed—creating a burden on working memory. In addition to the information requirements, participants received paper on which to record their conceptual model solutions. The conceptual modeling task requirement (to develop a conceptual model from a narrative description and a list of attributes) was consistent with the course and exam requirement at both the undergraduate and graduate level.

Additional measures served as controls of factors related to conceptual modeling performance. Two additional types of knowledge were measured: attribute aggregation knowledge (*AAK*) and knowledge content (*KC*). Participants received a randomized list of attributes (i.e., the attributes in the list were not grouped by entity) to recall, and attribute aggregation knowledge was inferred from the order in which participants recalled items in the list. For the attribute aggregation knowledge test, there were 35 possible attributes to recall. These attributes aggregated to a total of seven entities (cash, customer, inventory, purchase, purchase order, sale, and vendor). Each entity had five attributes: for example, customer number, name, address, phone number, and accounts receivable balance aggregated to the customer entity. The seven entities included resources, events, and agents from the revenue and acquisition business processes.

[8] Similar results obtain from an ANCOVA with undergraduate GPA, undergraduate GPA in major, total number of accounting courses completed, total number of undergraduate credit hours completed, and ACT score as covariates.

A knowledge content test measured whether participants had the prerequisite knowledge to perform the conceptual modeling task. The knowledge content test consisted of a series of questions about REA and E-R model constructs. In addition to providing assurance that the less-trained-in-REA participants possessed sufficient knowledge content to design a conceptual model, these data provided a control for differences in knowledge content.

An investigation of the knowledge-performance relationship requires consideration of other factors known to be correlated with conceptual modeling performance. For example, field independent individuals, as measured by performance on Oltman et al.'s (1971) Group Embedded Figures Test (*GEFT*), perform better at conceptual modeling (Dunn and Grabski 1998). The *GEFT* is a standardized paper and pencil test that contains a set of target figures ("simple forms") that must be located within a series of complex figures. Field dependence (Witkin et al. 1971; Oltman et al. 1971) is a type of cognitive style, or, "characteristic, self-consistent modes of functioning that individuals show in their perceptual and intellectual activities" (Witkin et al. 1971, 3). Consistent with Dunn and Grabski (1998), field dependence was measured by participants' performance on the *GEFT*. Witkin et al. (1971) have demonstrated the *GEFT* reliability and validity.[9] In addition to field dependence, class level was included as a covariate because factors resulting from class-level differences, such as motivation, ability, and unmeasured general knowledge differences, could also affect conceptual modeling performance.

Procedures

To control for order effects, Phases 1 and 2 of the experiment were counterbalanced; participants were randomly assigned to complete Phase 2 either before or after the free recall tasks described in Phase 1. Participants were informed that a complete design included entities, relationships, attributes, and cardinalities, and they had access to the design requirements for the duration of the task. Once participants were given the information requirements, they were allowed 90 minutes to complete their conceptual models. They completed both phases within two days.

For the attribute-list recall task, participants studied a list of attributes for four minutes. Following the study period, participants recorded their recall. Participants were allowed up to ten minutes to recall as many attributes as they could. After finishing the recall tasks, participants completed the *GEFT*. Participants then completed the untimed knowledge content test.

Variables and Data Coding

Related to Hypothesis 2, the following model is estimated:

$$CMP = \beta_0 + \beta_1 REA\_Recall + \beta_2 AAK + \beta_3 KC + \beta_4 GEFT + \beta_5 CLASS + \varepsilon \quad (1)$$

where:

CMP = Conceptual Modeling Performance (measured accuracy score from conceptual modeling task);

REA_Recall = REA Knowledge Structure (number of items recalled—measured during Phase 1 of experiment);

[9] However, Ford et al. (2002, 729) advocate using Riding's (1991) Cognitive Styles Analysis since it overcomes the *GEFT*'s limitation whereby "levels of field *dependence* are inferred from poor field-*independence* performance" (emphasis in the original).

AAK = Attribute Aggregation Knowledge (measured variable is *ARC* index—attribute clustering measure);
KC = Knowledge Content (measured variable is score from knowledge content test);
GEFT = Group Embedded Figures Test (measured variable—test of field dependence); and
CLASS = Dummy variable (1 for graduate student, 0 for undergraduate).

CMP is the dependent variable measuring conceptual modeling performance relative to a normative solution agreed upon by two experts in REA and conceptual modeling. The normative solution contained 345 possible points, with point values assigned as follows: entities ten points each, relationships six points each, attributes four points each, and cardinalities one point each.[10] For each participant, errors were subtracted from the 345 total possible points; therefore, the higher the score, the better the conceptual modeling performance.

AAK, *KC*, *GEFT*, and *CLASS* are control variables; *REA_Recall*, the independent variable for Phase 2, was discussed in Phase 1. Attribute-aggregation knowledge (*AAK*) was measured with Roenker et al.'s (1971) adjusted ratio of clustering measure:

$$\text{Adjusted Ratio of Clustering} = [R - E(R)]/[\max R - E(R)] \tag{2}$$

where:

R = total number of observed category repetitions;
E(R) = expected (chance) number of category repetitions = $[(\Sigma_i n_i^2)/N] - 1$;
n_i = number of items recalled from category I;
N = total number if items recalled; and
max R = maximum number of category repetitions (total number of items recalled minus the number of categories present in the recall).

This measures the degree of clustering, which ranges from -1 (no clustering) to 1 (clustering), with 0 indicating clustering due to chance.

KC measures REA and E-R model knowledge content ($0 \leq KC \leq 21$). Correct answers received one point. The first test question presented E-R symbols (for an entity, a relationship, a nonkey attribute, and a key attribute) and asked for an explanation of each symbol. The second question asked for examples of a resource, an event, an internal agent, and an external agent. The third question presented sets of correct and incorrect cardinalities and asked for identification of all incorrect sets. The fourth question depicted a relationship between sale and customer entities and asked for the default cardinalities. Finally, the fifth question asked for a narrative description of the cardinalities that participants provided in the fourth question.

GEFT (field dependence) was measured as accuracy scores on the Group Embedded Figures Test. *CLASS* is a dummy variable set to 1 for graduate participants and 0 for undergraduate participants; *CLASS* is used to control for unknown factors that may differ between the groups. For example, it is unlikely that the measures of knowledge content

[10] Certain errors have greater consequences (omitting an entity has greater consequences than omitting an attribute). Analysis indicates that the effect of weighting the errors versus not weighting them does not change the conclusions.

and knowledge structure could capture all of the knowledge related to task performance that could vary across participants. It is likely that graduate participants have other knowledge, abilities, and skills that may be associated with conceptual modeling performance. As a stringent test of the importance of REA knowledge structure in conceptual modeling performance, *CLASS* was included as a control variable in the regression of *CMP* on *REA_Recall*, *AAK*, *KC*, and *GEFT*. The coefficient on *REA_Recall* (or *REA_Recall2*) is hypothesized to be positive.

Results

Descriptive Statistics and Test of Hypothesis 2

Hypothesis 2 predicts that, after factoring out other determinants of conceptual modeling performance, performance will be positively correlated with REA knowledge structure. This hypothesis was tested using both correlation and multiple regression analysis. Data analysis revealed no significant order effects.

Table 2, Panel A, presents means, standard deviations, correlations, and covariances. The correlation between *REA_Recall* (and *REA_Recall2*) and *CMP* is in the predicted direction. Parameters of the regression model were estimated using ordinary least squares with *CMP* regressed on *REA_Recall* (and alternatively, *REA_Recall2*), *AAK*, *KC*, *GEFT*, and *CLASS*. However, using the Cook-Weisberg (1983) test for heteroscedasticity, the null hypothesis of constant variance was rejected. Therefore, a regression model with White (1980) corrected standard errors was estimated.[11] Table 2, Panel B, shows the parameter coefficient estimates, robust standard errors, White's (1980) t-statistics, and p-values. *REA_Recall* has a significant effect on conceptual modeling performance ($t = 2.00$, $p = .02$) while controlling for *AAK*, *KC*, *GEFT*, and *CLASS*, supporting Hypothesis 2. Similar results held for the alternative measure *REA_Recall2* ($t = 2.08$, $p = .02$). *CLASS* was strongly associated with conceptual modeling performance ($t = 5.78$, $p < .001$). Additional tests revealed no significant interactions. Sensitivity tests indicated the results were unaffected by the weighting of the dependent variable or by extreme observations.

When the regression was analyzed without *CLASS*, the *REA_Recall* coefficient remained significantly positive ($t = 5.5$, $p < 0.001$); REA knowledge structure was correlated with conceptual modeling performance (while controlling for attribute aggregation knowledge, knowledge content, and field dependence). However, by including *CLASS* in the regression model, it is apparent that after controlling for the effects of training and other potential differences between groups, REA knowledge structure still correlates with conceptual modeling performance.

V. CONCLUSION

The results indicate that as individuals' knowledge structures become more organized according to the REA pattern, accuracy in conceptual modeling significantly improves. To further clarify the point, this is not just a case of experienced modelers knowing more so they design better. Rather, knowledge *structure* matters. If: (1) the information requirements for a system are clear, and (2) modelers can read and understand the requirements, and (3)

[11] Multicollinearity was analyzed using the two-part process (based on condition indexes and the regression coefficient variance-decomposition matrix) explained in Hair et al. (1998, 220–221). This method revealed multicollinearity between the intercept and knowledge content (*KC*). However, knowledge content was kept in the model rather than having a correlated omitted variable problem. Multicollinearity would bias against finding results for the knowledge structure (*REA_Recall*) coefficient. All variance inflation factor values were less than 1.8.

TABLE 2
Descriptive Statistics, Correlations, Covariances, and Regression Results: Effect of *REA_Recall* on Conceptual Modeling Performance

Panel A: Descriptive Statistics, Correlations, and Covariances

Variable[a]	*M*	*SD*	Pearson Correlations[a] (two-tailed p-values) below the diagonal; covariances above: *CMP*	*REA_Recall*	*REA_Recall2*	*AAK*	*KC*	*GEFT*	*CLASS*
CMP	219.53	77.04	1.00	1,190.72	177.78	7.55	29.95	53.19	26.40
REA_Recall	46.47	28.31	.55 (<.0001)	1.00	88.38	2.87	12.11	29.36	8.55
REA_Recall2	13.72	4.74	.49 (<.0001)	.66 (<.0001)	1.00	0.74	1.34	1.84	1.21
AAK	0.40	0.37	.27 (<.01)	.27 (<.01)	.42 (<.0001)	1.00	0.03	0.04	0.06
KC	20.04	1.20	.32 (<.01)	.36 (<.001)	.23 (<.02)	.06 (<.58)	1.00	0.35	0.19
GEFT	13.73	3.94	.18 (<.09)	.26 (<.01)	.10 (<.34)	.03 (<.81)	.07 (<.48)	1.00	0.32
CLASS	0.46	0.50	.77 (<.0001)	.61 (<.0001)	.51 (<.0001)	.32 (<.01)	.30 (<.01)	.20 (<.05)	1.00

Panel B: $CMP = \beta_0 + \beta_1 REA\_Recall + \beta_2 AAK + \beta_3 KC + \beta_4 GEFT + \beta_5 CLASS + \varepsilon$

Variable	Predicted Sign	Coefficient	Robust Standard Error	White's t-statistic	One-tailed p-value
INTERCEPT (β_0)		26.09	99.45	0.26	.40
REA_Recall (β_1)	+	0.46	0.23	2.00	.02
AAK (β_2)	+	9.10	17.65	0.52	.30
KC (β_3)	+	6.02	4.98	1.21	.12
GEFT (β_4)	+	0.70	1.39	0.50	.31
CLASS (β_5)[b]	+	81.81	14.15	5.78	<.001

$n = 99$. $R^2 = 0.51$.
[a] Correlations with *CLASS* are Spearman correlations.
[b] Note when the regression is analyzed without *CLASS*, the *REA_Recall* coefficient remains significantly positive ($t = 5.5$, $p < 0.001$).

modelers know how to use conceptual modeling constructs, then they should create a correct conceptual model. These are the assumptions underlying almost all database texts on conceptual modeling. However, in spite of accumulated knowledge, until the knowledge becomes organized into a structure, design errors will occur because modelers may ineffectively structure information, or they may not know how to structure the information. Furthermore, domain knowledge acquired from daily-life observation and well-written information requirements does not necessarily have the abstract structure that is necessary for effective conceptual modeling (i.e., not any domain knowledge is sufficient). For example, all participants had some domain knowledge (i.e., of how a video-rental business works). But that domain knowledge was insufficient. Modeling economic exchanges requires REA knowledge structure. This research may be useful to people responsible for the training and education of conceptual modelers, especially those who traditionally have ignored domain-specific patterns. Ignoring such patterns eliminates an opportunity to structure knowledge.

Another contribution of this study is that it takes a first step toward identifying dimensions of knowledge relevant to conceptual modeling of AIS. Multiple dimensions of relevant knowledge were identified including REA knowledge structure, knowledge content, and attribute aggregation, and their effects on conceptual modeling performance were tested. This is significant because the tendency in accounting research has been to investigate experience-performance relations and infer the role of knowledge (i.e., very few studies have tested experience-knowledge and knowledge-performance relations directly in one study). However, as Libby (1995, 204) points out "even if experience-performance relations have been adequately demonstrated, we cannot understand their implications for decision improvement without understanding the knowledge differences that produce the performance differences."

The experiment includes limitations of context and setting. The use of nonequivalent groups is a potential threat to internal validity. An alternative experimental design could have included, for example, graduate students with only basic REA training and/or undergraduates with more than basic REA training. Related to the conceptual modeling task, participants were not required to design a relational database in third normal form. Although E-R models tend to produce normalized databases (see McCarthy 1979; Batini et al. 1992, 161), the link between conceptual models and databases must be addressed in future research. All constructs in this research were instantiated as single-item measures. Multi-item measures would increase measurement reliability and decrease the likelihood of monomeasure bias (Straub 1989). Furthermore, construct validity was not reconfirmed for latent variables. Further, it may be possible to improve the REA knowledge structure measure (e.g., through protocol analysis [Ericsson and Simon 1993]).

This research focused on the REA pattern. The free recall experiment and conceptual modeling problem were limited to the revenue and acquisition processes. Participants' knowledge structures might change if they learned additional patterns. Other domain-specific patterns exist and those patterns may be more, or less, generalizable than REA. The generalizability of a pattern may affect the time required to develop a knowledge structure. It is also unclear how the results for a conceptual modeling pattern may extend to other patterns such as object-oriented programming patterns.

This paper is a first step in a research program of understanding the role of memory in conceptual modeling performance. Future research should examine other patterns, settings, and modelers. Conceptual modeling is important, but people find it difficult and problematic (Batra et al. 1990; Goldstein and Storey 1990; Prietula and March 1991; Batra and Marakas 1995; Hitchman 1995; Wand and Weber 2002). The ultimate goal of conceptual modeling research is to learn how to build better quality information systems and how to decrease design errors and associated costs. However, it is unlikely that this goal will be reached without a more complete understanding of conceptual modeler cognition.

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