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An Investigation of Localization as an Element of Cognitive Fit in Accounting Model Representations

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ABSTRACT

Cognitive fit, a correspondence between task and data representation format, has been demonstrated to lead to superior task performance by individual users and has been posited as an explanation for performance differences among users of various problem representations such as tables, graphs, maps, and schematic faces. The current study extends cognitive fit to accounting models and integrates cognitive fit theory with the concept of localization to provide additional evidence for how cognitive fit works. Two accounting model representations are compared in this study, the traditional DCA (Debit-Credit-Account) accounting model and the REA (Resources-Events-Agents) accounting model. Results indicate that the localization of relevant objects or linkages is important in establishing cognitive fit.

Subject areas: Accounting Information Systems, Cognitive Fit, DCA Accounting, Localization, and REA Accounting.

INTRODUCTION

For several years researchers obtained mixed results in studies of user performance with tables and graphs. Vessey (1991) developed cognitive fit theory, which predicts that a correspondence between task and information presentation format leads to superior task performance by individual users. In several studies, cognitive fit theory has provided an explanation for performance differences among users across different presentation formats such as tables, graphs, and schematic faces (e.g., Vessey, 1991, 1994; Vessey & Galletta, 1991; Umanath & Vessey, 1994). Smelcer and Carmel (1997) and Dennis and Carte (1998) extended cognitive fit theory into the geographic information systems domain, using it to explain performance differences among users of map and table-based geographic information systems on adjacency, proximity, and containment tasks. Such studies have provided important contributions to the decision-making literature. Additional research is needed to gain a more complete understanding of how cognitive fit works and to use that understanding to provide designs for information systems that foster improved task performance.

Cognitive fit theory may help to explain performance differences among users of two alternative accounting models. Research has identified a trend in accounting information systems design of providing more information than allowed by the traditional double-entry bookkeeping model through the incorporation of characteristics of the Resource-Event-Agent (REA) accounting model (David, McCarthy, & Sommer, 1996). A benefit of these richer systems is that significant competitive advantages have been perceived by managers of organizations that possess REA-like systems (David, 1996).

In this paper, cognitive fit is extended to the domain of accounting models to provide evidence about the use of alternative accounting models and to gain insight as to how cognitive fit works based on localization (Larkin & Simon, 1987). The next section of this paper summarizes the two accounting models compared in this study. Subsequently, hypotheses are developed based on cognitive fit and localization. This is followed by a description of the research method employed and results of statistical tests. Finally, a discussion of the results of this study and suggestions for future research directions is presented.

ALTERNATIVE ACCOUNTING MODELS

Why are there alternative accounting models? Most business people are familiar with the traditional double-entry bookkeeping model originally documented by Luca Pacioli in 1494. This model uses journal entries with debits and credits to store dollar amounts in various general ledger accounts. We henceforth refer to this model as the Debit-Credit-Account, or DCA, accounting model. Fewer people are aware of the Resource-Event-Agent (REA) model, which provides a generalized framework for accounting information systems in a shared data (or database) environment (McCarthy, 1982). Indeed, many people hold the constructs of the DCA model to be necessary, natural phenomena rather than the artifacts that they really are. Dunn and McCarthy (2000) discussed the naturalness versus artificiality of DCA constructs and provided a history discussing why double-entry accounting was invented. They also provided reasons why it should be replaced with an accounting model more suited to current technological and economic circumstances. McCarthy (1982) was not the first to note the limitations of the DCA accounting model. Goetz (1939, 1949) and Schmalenbach (1948) complained about the inability of accounting systems to provide necessary information for non-financial accounting purposes. Colantoni, Manes, and Whinston (1971) and Everest and Weber (1977) attempted to create "database accounting systems" and concluded that the artifacts of the DCA model were not conducive to computerization (for a more complete description of events accounting, database accounting, semantically modeled accounting and REA accounting research, see Dunn & McCarthy, 1997).

The REA model was originally proposed by McCarthy (1982) as a way to overcome limitations inherent in the traditional DCA model on which the traditional double-entry accounting systems are based. These limitations include limited dimensionality, inappropriate classification schemes, too much aggregation of stored data, and limited integration with other functional business areas. Traditional DCA systems include only monetary measures and are unable to capture other necessary business information such as reliability, timeliness, quality, etc. The chart of accounts identifies the only way data can be stored, which can lead to data being discarded or classified in such a way that nonaccountants (and at times even accountants) cannot discern its true nature. By definition, traditional DCA systems store summarized results of economic events, while many decision makers require disaggregated data or results summarized in a manner other than that imposed by the accounting system. Thus, most companies maintain separate systems for other functional business areas such as logistics, production management, marketing, inventory control, and human resources. This separation leads to redundant and inconsistent data. Present-day enterprise resource planning (ERP) systems are more like REA-modeled systems than they are like DCA-modeled systems (David et al., 1996). O'Leary (1999) compared information about the market-leading commercial ERP software package (SAP) with REA and determined that SAP is largely consistent with REA, but that it contains implementation compromises due to accounting artifacts. Such systems do not fully specify all entities and relationships required for the complete REA pattern; thus, they are not epistemologically adequate (Geerts & McCarthy, 1992).

The REA model is a semantic model of an enterprise's information system. A semantic data model provides expressiveness, simplicity, realism, and relevance (Hammer & McLeod, 1981; Navathe, 1992; Dunn & McCarthy, 1997). That is, the various data and relationships in a semantic data model effectively communicate the phenomena of interest, users can readily understand the model, objects in the model correspond closely to real-world phenomena, and the actual value added activities or processes are modeled. The REA model provides a direct relationship between the model and reality, similar to that of a road map, and the highways and streets that are represented on that map. Users perceive REA-based systems to be more semantically expressive than the DCA-based systems (Dunn & Grabski, 2000).

The REA model is able to provide information that "modern management accounting systems" require. For example, O'Brien and Sivaramakrishnan (1996) simulated a traditional accounting system and a cycle-time accounting system for coordinating order processing and production scheduling runs, and they found cycle-time accounting resulted in superior coordination. DCA accounting systems require a separate information system to be built (with resultant redundancies and inconsistencies), whereas the required cycle-time information can easily be incorporated into an REA accounting system. This could be done using techniques presented by Grabski and Marsh (1994), who demonstrated the integration of activity-based costing (ABC) into an REA-based system, or by Denna, Jasperson, Fong, and Middleman (1994), who demonstrated the modeling of conversion processes within an REA system.

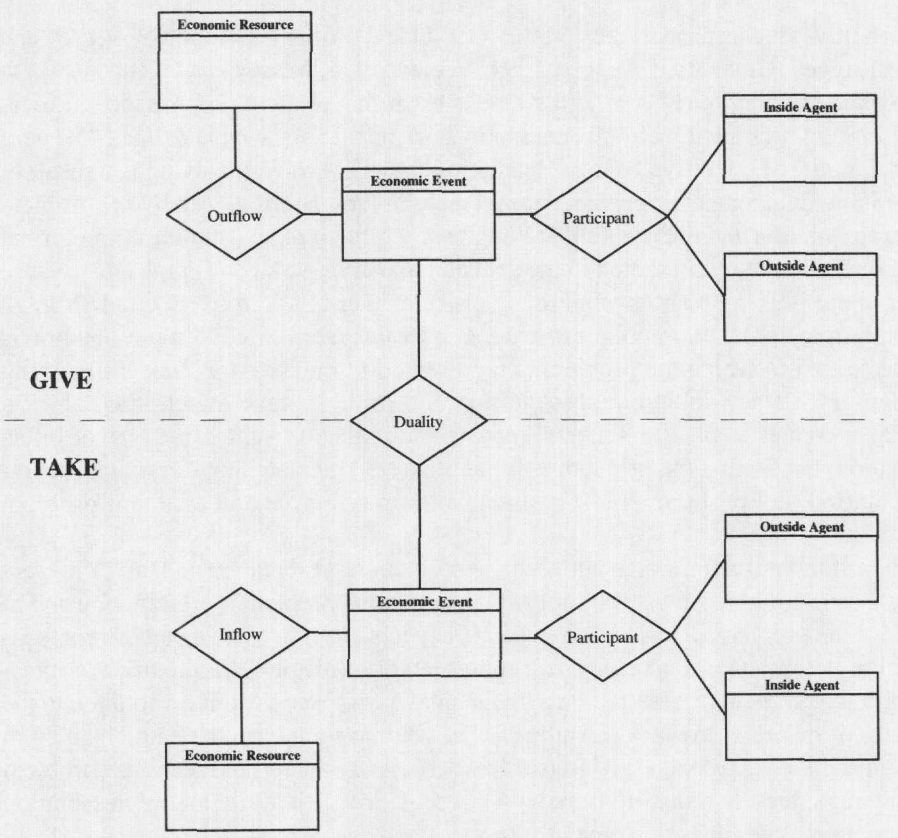
Appendix A contains a sample REA-modeled business process. Various representation formats have been used for the REA model, including entity-relationship (E-R) diagrams, Nijessan Information Analysis Modeling (NIAM) diagrams, and object-oriented diagrams (see Geerts & McCarthy, 1991). We limit our brief discourse to REA using E-R diagram notation, since that notation has been used most often in prior literature. The basic model as proposed by McCarthy (1982) consists of two related economic "give and take" events, and the related economic resources and agents (see Figure 1). An enterprise will give up an economic resource through some economic event in order to obtain some other economic resource in another related economic event. Economic events are central to this approach and help to distinguish this model from other data models developed from a computer science orientation. The economic events of the enterprise are related via stock-flow relationships to the economic resources involved in the events. The people involved in the events are depicted as the inside and outside economic agents, with the inside agents generally being employees of the enterprise and the outside agents typically being parties involved in an "arm's length" transaction.

It is important to clarify the difference between entity-relationship modeling in general and REA modeling. The entity-relationship notation is a tool that may be used to represent an REA model of an enterprise. REA modeling provides a structured approach for modeling enterprises using repeated, integrated instances of the REA pattern; the full REA modeling requires complete adherence to the template for all business activities (Geerts & McCarthy, 1992). The original REA model was extended by Geerts and McCarthy (2000), who proposed it as an enterprise ontology. When modeled using entity-relationship notation, the REA ontology requires that events be modeled as entities and connected to related events, resources, and agents, whereas in the more traditional entity-relationship model these events may be treated as associative entities or as relationships (Hoffer, George, & Valacich, 1999).

In Appendix A, *G&A Service & Supplies Acquisition* and *Cash Disbursement* represent the two causally related economic events: the acquisition of general and administrative services and supplies, and the payment of cash for those services and supplies. *Supplies Inventory* and *Cash* are the economic resources that are taken and given up, respectively, by these events. *Receiving Clerk* and *Cashier* are the internal agents involved in these events; *Vendor* is the external agent involved in these events. The REA model also allows for non-economic events and other relevant entities and relationships to be specified. For example, *G&A Service Type* is a type-image entity used to represent information regarding standard costs of services typically purchased. *G&A Service & Supplies Order* is a commitment event that represents unfilled purchase orders for services and supplies. Information about commitments and resource-type images is typically stored in non-integrated form in traditional DCA-based accounting systems, whereas they are directly integrated into REA-based systems.

Additional information also is presented in the REA model, such as how each entity participates in each relationship. Minimum participation rules identify the minimum number of times an entity can participate in a relationship, and maximum participation rules identify the maximum number of times an entity can participate in a relationship (per Batini, Ceri, & Navathe, 1992). For example, in Appendix A, the relationship between G&A Service & Supplies Acquisition (1,1) and Vendor (0,*N*) indicates that a G&A Acquisition cannot be entered into the system without

Figure 1: REA template (McCarthy, 1982).



having a corresponding vendor (minimum = 1), and it can have at most one corresponding vendor (maximum = 1). A Vendor can be entered into the system without a corresponding acquisition (minimum = 0), and a vendor can be associated with multiple acquisitions (maximum = *N*). Structural constraints such as these encompass firm-specific policies and can be used to enforce business rules. For example, for a cash disbursement to occur, there must be a G&A receipt, an existing vendor, an existing cash account, and a cashier to write the check. Information represented by entities and relationships in an REA diagram is often implemented as relational database tables, and the table attributes are provided in the REA-modeled system in this study. The disaggregated "raw" data about each event and the associated resources incremented (decremented), and inside and outside agents involved, are captured without any filtering of the data.

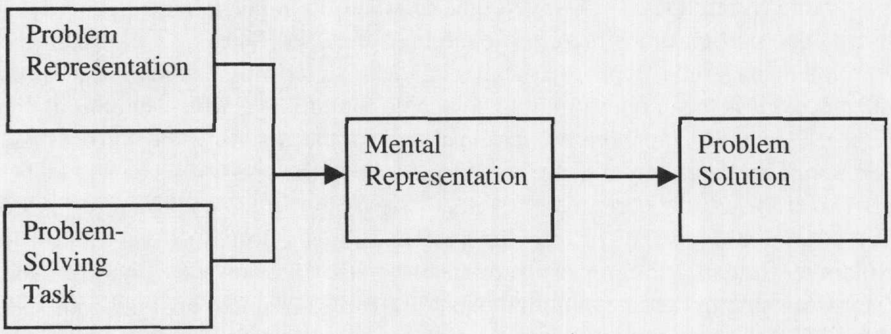
HYPOTHESIS DEVELOPMENT: COGNITIVE FIT AND LOCALIZATION

Cognitive fit was proposed by Vessey (1991) and further developed by Vessey and colleagues (Umanath & Vessey, 1994; Vessey, 1994; Vessey & Galletta, 1991) to explain the previously conflicting results regarding relative performance of users who were presented with information in a graphical versus table format. The general model of cognitive fit is presented in Figure 2. Problem solving is a result of an individual's mental representation which, in turn, is influenced by the problem representation and the problem-solving task. Problem representation is the format of the information presented to the decision maker (e.g., tables, graphs, lists, etc.). Problem Solving Task is what the decision maker is asked to accomplish (e.g., bankruptcy prediction, point estimate, trend value, etc.). Mental representation is the format in which the problem is represented in the decision maker's working memory. If the problem representation and problem task match, the decision maker creates a consistent mental representation that uses the same type of information, facilitating the problem-solving process. The matching of problem representation and problem-solving task results in effective and efficient problem solving.

If there is not a match between the problem representation and task, different cognitive strategies must be employed to act on the problem representation and to solve the problem. The decision maker is expected to formulate a mental representation based either on the problem representation (resulting in the need to transform the problem representation in the mental workspace to derive a solution to the task) or based on the task (resulting in the need to transform the data obtained in the problem representation). Regardless, efficiency and effectiveness of problem solving is less than that of users who are provided with a problem representation that emphasizes the same type of information as the task.

The REA accounting model and the DCA accounting model are alternative representations that form the basis of accounting systems. The REA accounting model was designed to capture the underlying reality of the environment being modeled, including financial and non-financial activities, parties to the activities, and resources involved (McCarthy, 1982). Dunn and McCarthy (1997) claimed that an important characteristic of REA is its semantic expressiveness; Dunn and Grabski (2000) presented support for this claim. The DCA model was originally developed to capture the underlying reality of a restricted set of characteristics of financial transactions, thus, by definition only models a limited portion of the environment. The DCA model is often implemented as a series of account listings and is predominantly symbolic in nature, that is, discrete values (account names) are presented and relationships among accounts are only directly presented in symbolic form in the journal entries themselves. There is no overall representation of secondary and later relationships, whereas these are depicted in the REA representation. The REA model can be implemented using a variety of technologies including artificial intelligence and object-oriented programs (Chen, McLeod, & O'Leary, 1995). It has been portrayed most often as a combination of entity-relationship (E-R) diagrams and relational database tables. In this form, the REA model is predominantly spatial in nature, revealing associations between objects.

Figure 2: General problem-solving model of cognitive fit (Vessey, 1991).



The DCA model has been portrayed most often as a series of ledger accounts and journals, both in manual and computerized systems. In this form it is predominately symbolic in nature.

The REA model, while often presented by accounting cycles (e.g., the revenue cycle, the acquisition cycle, etc.), does not differentiate among artificial classifications such as assets, liabilities, owners equity, revenues, and expenses. In fact, some items such as accounts receivable and accounts payable that are maintained as balances in the DCA model are derived only when needed in an uncompromised REA system (McCarthy, 1982, 1984). The DCA model is characterized by the chart of accounts, ledgers, and journals. It is generally presented in a textual format, and is often presented with the use of indexed hierarchical lists. The chart of accounts is arranged (by convention) according to assets, liabilities, owner's equity, revenues, and expenses.

The findings of cognitive fit research (Dennis & Carte, 1998; Sinha & Vessey, 1992; Smelcer & Carmel, 1997; Umanath & Vessey, 1994; Vessey, 1991, 1994; Vessey & Galletta, 1991) may apply to the users of REA and DCA accounting models. However, an important difference exists. In the cognitive fit literature, relatively "pure" presentation formats were used—graphs, maps, or schematic faces, which emphasized spatial relationships among data points; and tables, which emphasized symbolic or discrete data values. The REA and DCA accounting models are less distinct in format. The REA model as implemented with E-R diagrams and relational tables, is both spatial and symbolic in nature. The DCA model's ledger accounts are symbolic in nature, yet the chart of accounts provides an indexing mechanism not found in tables such as those used by Vessey and colleagues (Sinha & Vessey, 1992; Umanath & Vessey, 1994; Vessey, 1991, 1994; Vessey & Galletta, 1991). An advantage of graphical representations over tabular formats is the ability to represent relationships among various objects of interest. That is why graphs typically are preferred for trend analysis. Similarly, the REA model is able to represent relationships that exist within business processes.

Cognitive fit research has examined task characteristics and problem representations in general terms: spatial and symbolic. If a representation enables the decision maker to focus on relevant task factors by means of presenting complete, simple, and regular relations in patterns with which the decision maker is experienced, then cognitive fit will likely occur and task performance will be enhanced. Larkin and Simon (1987) observed that an attention management system determines what portion of a structure is examined and used. They said the "nature of attention management depends crucially on the linkages provided in the data structure since this is the only information available for guiding shifts in attention" (pp. 67-68). Essentially, if the representation allows for the "localization" of focus (i.e., attention is appropriately directed to a limited area), then performance will be better. This may help to explain the results of Agarwal, Sinha, and Tanniru (1996), who extended cognitive fit into the system analysis domain in an attempt to explain performance differences on process- versus object-oriented analysis tasks. They were able to demonstrate that users of process-oriented analysis tools performed better on process-oriented tasks than on object-oriented tasks; however, they found no difference for users of object-oriented analysis tools on process- and object-oriented tasks. Agarwal et al. (1996) was an important study in that it didn't use a display format per se, but instead matched a type of tool to a type of task. In analyzing their results, they noted that some subtasks went completely unconsidered (unanswered) by most users of one tool, and there were other subtasks that were missed by most users of the other tool. This suggests localization as an attention-directing mechanism may be an important facet of cognitive fit.

The REA model depicts relationships among business events, agents, and resources. In order to reduce cognitive strain and because of physical limitations (paper and font size), the diagrams are often presented in parts based upon business processes; for example, sales/collection, acquisition/payment, etc. Some tasks users might perform are contained within a single diagram, and the REA template pattern may immediately draw users' attention to the relevant relationships. Other tasks may be contained within a single diagram, but the attention-directing mechanism is less salient, and users must draw on past experiences with the pattern. Still other tasks require users to integrate multiple cycle diagrams to obtain all relevant information. This presents some interesting issues. Based on Larkin and Simon (1987), greater localization results in better performance. Experience is also necessary for localization to result in attention direction. If the required information is localized to one place within a representation but the user does not have the experience to recognize the localization, the user's attention will not be directed to that part of the representation.

Different degrees of attention direction exist. For example, within an REA diagram in entity-relationship format, a task may require information that exists within a single relationship on a diagram and, thus, can be found within a single table. Experience needed to recognize the localization is minimal, thus, experienced and novice users could be expected to perform equally well using such a representation. Alternatively, a task may require information that exists within a cluster of two related entities, thus requiring attributes of each entity and of the relationship. This would require use of three tables, and may require joining the tables together. The experience needed to recognize the localization and to use it effectively is greater. Therefore, experienced users could be expected to perform better than novice users. If localization is minimal or does not exist, attention is not directed by the representation itself, and performance could be expected to be dependent on experience rather than on the type of representation provided. For example, if a user needs to examine multiple REA diagrams or other types of documents, location of one relevant piece of information may not suggest the need to examine other related diagrams or documents. The decision maker is not prompted, but must, instead, recognize from past experience the need to look elsewhere. Thus, when attention needs to be directed across multiple diagrams or documents, performance will likely degrade because users tend to perceive a single diagram or document to represent complete information.

Hypotheses 1-3 are proposed based on the above discussion.

H1: REA users will be more accurate than DCA users regardless of experience for tasks that direct users to a single relationship within one business process in an REA-modeled system, but which are not supported by localization in a DCA-modeled system. That is, there will be a main effect for accounting model but no main effect for experience.

H2: REA users will be more accurate than DCA users for tasks that require the use of multiple entities joined by a relationship within one business process in an REA-modeled system, but which are not supported by localization in a DCA-modeled system. Further, experienced users within the respective treatments will be more accurate than novice users. That is, there will be main effects for both accounting model and experience.

H3: Experienced REA and DCA users will be more accurate than novice REA and DCA users for tasks that cross multiple business processes in an REA-modeled system and for which localization is not present in either the REA or the DCA-modeled system. That is, there will be a main effect for experience but no main effect for accounting model.

Cognitive fit predicts that users of information that is consistent across problem and task representations will perform more quickly than users of inconsistent information, because of increased cognitive costs to process the information. Thus, task completion time is hypothesized to behave inversely to task accuracy as proposed above, as reflected in H4-H6.

H4: Task completion time will be lower for REA users than for DCA users regardless of experience for tasks that direct users to a single relationship within one business process in an REA-modeled system, but which are not supported by localization in a DCA-modeled system. That is, there will be a main effect for accounting model but no main effect for experience.

H5: Task completion time will be lower for REA users than for DCA users for tasks that require the use of multiple entities joined by a relationship within one business process in an REA-modeled system, but which are not supported by localization in a DCA-modeled system. Further, experienced users within the respective treatments will be faster than novice users. That is, there will be main effects for both accounting model and experience.

H6: Task completion time will be lower for experienced REA and DCA users than for novice REA and DCA users for tasks that cross multiple business processes in an REA-modeled system and for which localization is not present in either the REA or the DCA-modeled system. That is, there will be a main effect for experience but no main effect for accounting model.

Prior studies have not investigated the effect of cognitive fit on user confidence. It would seem that users' confidence in their responses should increase with accuracy. Although other studies, such as Dickson, Senn, and Chervany (1977), found an inverse relationship between accuracy and confidence, the following exploratory hypotheses are proposed.

H7: REA users will be more confident than DCA users regardless of experience for tasks that direct users to a single relationship within one business process in an REA-modeled system, but which are not supported by localization in a DCA-modeled system. That is, there will be a main effect for accounting model but no main effect for experience.

H8: REA users will be more confident than DCA users for tasks that require the use of multiple entities joined by a relationship within one business process in an REA-modeled system, but which are not supported by localization in a DCA-modeled system. Further, experienced users within the respective treatments will be more confident than novice users. That is, there will be main effects for both accounting model and experience.

H9: Experienced REA and DCA users will be more confident than novice REA and DCA users for tasks that cross multiple business processes in an REA-modeled system and for which localization is not present in either the REA or the DCA-modeled system. That is, there will be a main effect for experience but no main effect for accounting model.

Prior cognitive fit studies have not reported data regarding the effect of cognitive fit on decision maker satisfaction or perceived ease of use. If the problem representation and task do not match, the decision maker must either reformulate the mental representation based on the problem representation or reformulate the mental representation based on the task. In either case, the decision maker should be less satisfied and perceive it to be more difficult because of the additional cognitive processing. Consequently, the following hypotheses are posed:

H10: When there is a high degree of cognitive fit between the accounting model and tasks performed, decision makers will perceive the accounting model as easier to use than when a low degree of cognitive fit is present.

H11: When there is a high degree of cognitive fit between the accounting model and tasks performed, decision makers will be more satisfied with the accounting model than when a low degree of cognitive fit is present.

RESEARCH METHOD AND RESULTS OF STATISTICAL TESTS

A laboratory experiment was conducted to test the hypotheses. Experienced and novice participants were randomly assigned to two groups. One group received the REA model documentation, which included entity-relationship diagrams for the following business processes: Sales/Collection, Repair Services/Collection, Sales Returns, General & Administrative Supplies & Services Acquisition/Payment, Inventory Acquisition/Payment, and Inventory Returns. The diagrams also included the resulting relational table structures, with primary keys identified and all attribute names (see Appendix A). The other group received the DCA documentation, which included the complete chart of accounts, with accounts classified as current assets, non-current assets, current liabilities, non-current liabilities, owners' equity, revenues, and expenses (see Appendix B). All participants received a set of sample source documents for that company in order to ensure they had an understanding of the types of transactions in which the company is involved and which they could use in formulating their task solutions (see Appendix C). The research instruments were pre-tested, and appropriate modifications were made prior to their administration. The REA and DCA documentation were based on the same company, and both sets of system documentation (i.e., the combination of the accounting model and source documents) contained all information needed to complete the experimental tasks.

Participants were required to explain how they would obtain an answer to a particular task using either the DCA- or REA-based system. The tasks required varying degrees of knowledge of relationships among data elements. The rationale behind this approach was to have participants figure out how to obtain the data rather than actually calculating an answer. All necessary information is available in each system's experimental materials; it is simply in different formats. This approach is superior to having participants use a "real" system based on either DCA or REA principles that may or may not be amenable to the tasks (thus "biasing" the experiment such that the tasks cannot be completed using either DCA or REA). It is also superior to requiring participants to obtain point estimates or totals because then mathematical abilities and other factors may confound results. For example, obtaining a correct dollar or number answer may or may not indicate the participant actually knew what they were doing; rather, the correct answer could be the result of a "lucky guess," or because errors made just happened to result in the same answer. Instead, by having the participants completely specify how they would obtain the needed information, the actual knowledge and ability can be assessed and is subsequently reflected in the accuracy score. This approach allows the "black box" of processing as conducted by the participants to be partially "opened" and examined. While all the thought processes of how participants determined how to obtain the answer are not acquired (to do so would require a think aloud protocol analysis technique as described by Ericsson & Simon, 1993, with the instrument administered individually to each participant), we can at least glimpse into what the participants thought were the correct processes. Furthermore, the participants only need to have a basic understanding of either the DCA or REA system to successfully perform the tasks in this experiment, rather than requiring knowledge of a specific software implementation.

The participants' task solutions were rated for accuracy (discussed below). Data were also collected as to their task completion time and confidence. After completing all tasks, participants were asked to evaluate their perceived ease of use and satisfaction with the system.

Participants

Ninety-eight undergraduate students and 22 MBA students participated in the experiment for class credit. The undergraduate students were enrolled in a senior-level accounting information systems course (their first) and had not been exposed to REA conceptual modeling techniques in previous courses. These participants were familiar with accounting concepts, having completed an average of six accounting courses. The MBA students, who were specializing in business information systems, were enrolled in an advanced database design course. Students taking this course had already completed one undergraduate-level and two other graduate-level business information systems courses. They had used the REA conceptual modeling material in their previous courses and were using it again in their advanced database design course. These students also had completed an average of eight accounting courses; thus, they were also experienced with accounting concepts and the DCA model. The undergraduate students serve as the novice user group, given their relative inexperience with the REA model; the MBA students serve as the experienced user group. Demographic data for both groups are reported in Table 1. There were no significant differences between the two inexperienced (experienced) groups based on age or years of work experience. There was a difference in gender ($p < .065$) between the novice and experienced groups; there were also differences in field independence ($p < .036$) and gender ($p < .044$) within the novice treatment groups.

Tasks

All participants answered the question of how they would obtain data (without actually calculating the dollar or number value) from their accounting information systems if they needed to perform each of the following six tasks:

1. Determine gross sales for one product line for a particular period of time.
2. Determine whether the company makes partial payments for services acquired.
3. Determine whether the company needs short-term borrowing for the next month.
4. Determine revenue by inventory stock number.
5. Determine the average delivery time for each vendor.
6. Create a bonus program for the company's sales representatives.

Table 1: Participant demographic statistics mean (standard deviation) values.

	REA Novice	DCA Novice	REA Experienced	DCA Experienced
Number of participants [female]	49 [29]	49 [19]	11 [3]	11 [3]
Age	22.5 (2.62)	22.8 (4.19)	23.4 (3.31)	23.6 (2.95)
Number of accounting classes taken	6.1 (1.68)	6.6 (2.10)	8.0 (3.05)	8.2 (2.60)
Years of work experience	3.28 (2.94)	3.24 (3.90)	4.0 (3.32)	2.36 (2.87)
Field independence (GEFT score)	12.73 (3.92)	14.31 (3.39)	12.45 (5.54)	13.36 (3.50)

These tasks are based upon both financial and managerial problem types. In fact, the managerial tasks are representative of the tasks (e.g., data disaggregated by product line or delivery time by vendor) that "modern manufacturing" practitioners and researchers (e.g., Anderson & Lanen, 1998; Foster & Gupta, 1994; Kaplan, 1988, 1990; Nanni, Dixon, & Vollman, 1992; O'Brien & Sivaramakrishnan, 1996) have cited as problems with "traditional" accounting information systems. These tasks are also representative of the tasks that managers and other users of information systems will encounter. Even if a "modern" system captures the requisite data at a disaggregated level, the information may not exist in a pre-defined reporting format. Many tasks are the result of information needs that were unplanned when the information system was developed. Hence, it is important for the users of the information system to easily obtain the needed information. The question is really "How easy is it for people (managers, clerks, etc.) to create the query for these tasks given the underlying accounting model?" If the underlying system does not provide the appropriate attention-directing mechanisms, the users are less likely to get the correct answer, and the system is less likely to actually be used (something that is well documented with "traditional" accounting systems).

In the selection of tasks to be used in this study, a trade-off was made. It was determined during pre-testing that six tasks were the maximum number of tasks that could be completed by the participants within the time period available. At this point the tasks could have involved those that test both the efficacy of cognitive fit within the DCA model (i.e., tasks that should be facilitated with DCA and not REA) and of cognitive fit within the REA model. However, a decision was made to more fully test the REA-based tasks and include two of each type of task type (i.e., localization and cognitive fit contained within a single relationship, contained between two entities and the associated relationship, or no localization at all). This allows for a more convincing test with respect to the efficacy of the REA model representation since two different tasks having the same underlying structure, rather than only one, were presented. This provides more compelling evidence (multiple tasks based on the same task type) rather than a single task for which it could be claimed that the result is due to random effects. Further, this does not affect the basic nature of the hypotheses, which address the nature of attention directing and experience aspects with respect to cognitive fit.

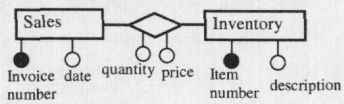
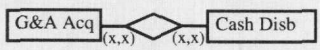
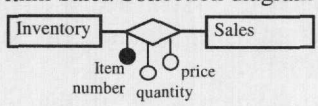
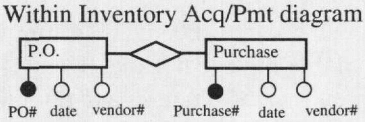
These tasks are described and classified below as to whether a higher degree of cognitive fit is expected with the REA or the DCA model, and as to what extent localization for each task is present within each representation. Figure 3 summarizes the REA versus DCA representations of the six tasks.

Task 1 requires the determination of total gross instrument sales for the period January 1 to April 30. Because the company had revenues from multiple product lines (instrument sales, accessory sales, and instrument repairs), the data cannot be determined as a single point value; rather, it requires the use of disaggregated data. The chart of accounts does not separate sales by product line, thus, in the DCA-modeled system the information must be obtained from the source documents. In the REA-modeled system the information required is localized to a single business process diagram. The solution must explain that to retrieve the information a user would need to join the sale table to the inventory table through the S-I table, which represents the relationship between sale and inventory. The user would be directed to those three tables via the relationship between the sale and inventory entities on the Sales/Collection diagram. The user must use the date attribute from the sale table to obtain the appropriate subset of sale transactions and then join across the three tables to isolate those inventory item numbers that represented instruments. Next, the user must multiply the quantity and price to get instrument line item totals and then sum them to get total gross instrument sales. Therefore, there is moderate localization to a *single entity-relationship cluster* in a single business process diagram in the REA-modeled system and no localization in the DCA-modeled system.

Task 2 requires the determination of whether the organization makes any partial payments for general and administrative services. This task requires a focus on the relationship between cash disbursement and general and administrative services received. The DCA system chart of accounts contains the accounts payable account, but that does not convey information as to whether partial payments are made. Source documents for G&A service and supply acquisitions and the corresponding checks must be compared. In the REA system, the structural constraints of the relationship between the G&A Service & Supplies Acquisition and Cash Disbursement entities identify the business rule that allows RSW to make partial payments. This task is supported by strong localization to a single relationship in a single business process (G&A Acquisition/payment) in the REA-modeled system but is not supported by localization in the DCA-modeled system.

Task 3 requires the determination of whether the organization needed any short-term borrowing for the next month. This task requires knowledge of relationships among cash and the elements that cause it to increase or decrease. In the DCA system, discrete data values are available for the current cash balance, current assets, and current liabilities. However, there are no discrete values available for other factors such as forecasted revenues and expenditures. In the REA-modeled system, relationships among cash and the elements that cause it to increase or decrease are available, but as with the DCA-modeled system, no discrete values are available for factors such as forecasted revenues and expenditures. Users must examine all six business cycle diagrams to determine economic events that increase and decrease cash. Further, the data values such as current assets and liabilities that are already aggregated in the DCA-based system must be derived from

Figure 3: Summarization of REA and DCA representations for tasks.

Hypothesis Tested	Task	REA	DCA
H2	Task 1 (Gross instrument sales)	Within Sales/Collection diagram 	Chart of accounts points to sales account, not separated by instrument versus other sales; Sales invoice form contains dollar amount as total of line-item detail
H1	Task 2 (Partial payments for G&A)	Within G&A Acq/Pmt diagram 	Chart of accounts does not help; purchase orders for G&A acquisitions must be compared to checks written for those orders
H3	Task 3 (Short-term borrowing needs)	Across multiple diagrams; Need to consider all events that result in cash receipts or cash disbursements	Chart of accounts classifies accounts as current assets, long-term assets, current liabilities, long-term liabilities, equity, revenue, and expense
H1	Task 4 (Revenue by stock number)	Within Sales/Collection diagram 	Chart of accounts points to sales account, does not contain disaggregate enough data to separate by stock number; must use sales invoice form
H2	Task 5 (Average delivery time)	Within Inventory Acq/Pmt diagram 	Chart of accounts contains no purchase order information; purchase orders must be compared to receiving reports
H3	Task 6 (Bonus plan)	Across multiple diagrams; Need to consider all events for which salespeople are responsible	Chart of accounts points to sales account, is not disaggregated by salesperson; sales call reports, customer orders, repair service orders and invoices, sales invoices, credit memos, and customer payments can be considered

Note: Attributes were not shown directly on the E-R diagrams; participants had to identify which relational tables represented the entity-relationship clusters noted in this figure and obtain the attributes from those tables. Showing the attributes connected to the diagram (including the foreign key vendor# for Task 5 and the Item Number part of the concatenated primary key for the Inventory-Sales relationship table for Task 4) is done only for purposes of illustrating the different hypothesized degrees of localization for the different tasks.

base transactions in the REA-based system. This task is not supported by localization in either the REA or the DCA-modeled system.

Task 4 requires the determination of revenue by inventory stock item number. This task requires knowledge of the relationship of products and sales and the use of disaggregated data. This information must be obtained from source documents in the DCA system, as the chart of accounts does not separate sales for each specific inventory item. In the REA system, a user must examine the Sales-Inventory relationship and use the attributes of that relationship to determine the solution (sort by inventory item number, multiply price by quantity, and sum within each item number). This task is supported by strong localization to a single relationship in a single business process (sales/collection) in the REA-modeled system but is not supported by localization in the DCA-modeled system.

Task 5 requires the determination of the average delivery time for the organization's vendors. This task requires information about the purchase order events and about the purchase delivery events that are related to the purchase order events. Traditional DCA systems consider purchase orders to be non-accounting events, as they have no immediate effect on assets, liabilities, or equities. Thus, source document details must be used for this task. In the REA system, the purchase order information is available in the Purchase Order entity table, and the purchase delivery information is available in the Purchase entity table. Information needed for this task is contained within a single business process (inventory acquisition/payment) in the REA-modeled system and is supported by moderate localization to a single entity-relationship cluster. The task is not supported by localization in the DCA-modeled system.

Task 6 requires the determination of information to create a bonus program for the sales representatives. This requires knowledge of the relationship between salesperson and events (e.g., sales call, sale order, sale, sale return, repair service), resources (e.g., inventory), and other agents (e.g., customer). In the REA system, these relationships are available but are not localized. The user would need to locate the salesperson entity on several diagrams and trace to several different relationships on each diagram. In the DCA-based system, the relationships are not emphasized, and a discrete data value is not available. The user must recognize the accounts that a salesperson's behaviors might affect and must also realize that some non-economic events involve salespeople and should be considered in developing a bonus plan. The non-economic event details must be obtained from the source documents in the DCA-based system. This task is not contained within a single business process in the REA-modeled system and is not supported by localization in either the REA or the DCA-modeled system.

Variables

Independent variables

Accounting Model was the between-subjects independent variable manipulated in this study. One group of participants used the REA accounting model; the other used the DCA accounting model. *Experience* was determined based on whether the participants were in their first data-modeling course (i.e., were undergraduate students) or had previously taken data-modeling courses that explicitly taught

REA modeling (i.e., the graduate students). *Task* was the within-subjects independent variable. Each participant completed each of the six tasks; there were two tasks in each of three categories, with varying degrees of localization as described in H1-H3. The task order was not randomized across participants; however, the order of the tasks employed to test H1 and H2 was counterbalanced.

Dependent variables

The dependent variables measured in this study are *Accuracy, Task Completion Time, User Confidence, Perceived Ease of Use*, and *User Satisfaction.* To measure *Accuracy,* a model solution was developed, and specific grading criteria were agreed upon and applied by two graders. The model solutions and grading criteria for Task 1 are presented in Appendix D; similar models and criteria were developed for each of the other tasks prior to grading the solutions. Each participant's solution was evaluated relative to the model solution by two graders using the grading criteria. The graders scored all participants' solutions for one task and then moved on to the next task, rather than scoring all tasks for one participant and then moving on to the next participant. Possible scores for each task were 0, 25, 50, 75, and 100. Once both graders had independently computed scores, the scores were compared and any differences reconciled. Interrater reliability before reconciliation of differences was .92. *Task Completion Time* was measured as the number of minutes participants spent completing a task. At the top of each task page, participants were reminded in writing to record their starting time. At the bottom of each task page there were written reminders for them to record their stopping time before going on to answer further questions.

User Confidence was measured separately for each task using a continuous scale anchored at 0% (*extremely unconfident*) and 100% (*extremely confident*). *Perceived Ease of Use* and *User Satisfaction* were measured for the information system taken as a whole (either the DCA-based system or the REA-based system) after the participants completed all of the tasks. *Perceived Ease of Use* was measured using these five 7-point Likert scale questions adapted from Davis (1989).

1. I found the accounting information system structure *cumbersome* to use.
2. Using the accounting information system structure was *frustrating.*
3. Using the accounting information system structure required *a lot of mental effort.*
4. The accounting information system structure was *clear and understandable* to me.
5. Overall, I found the accounting information system structure *easy to use.*

The original instrument has been used in prior studies, as have adaptations, with reasonable reported reliability (Cronbach's alpha has ranged from .83 in Batra, Hoffer, and Bostrom (1990) to .934 in Amer (1993); for the current study, alpha was .84). *User Satisfaction* was measured using the four 7-point Likert scale questions presented in Seddon and Yip (1992), who reported reliability of .95. Seddon and Kiew (1994) reported reliability of .91, and reliability of .92 was obtained in the current study. The four questions, adapted to this study's context, were as follows.

1. How adequately do you believe the accounting information system structure meets the information needs that you were asked to support?
2. How efficient is the accounting information system structure for providing the information you needed?
3. How effective is the accounting information system structure for providing the information you needed?
4. Overall, how satisfied are you with the accounting information system structure for providing the information you needed?

To gain better insight as to the effects of localization on users' cognitive processes, users would ideally have completed these questionnaires after each task. Operationally, it would have been difficult to ask the participants to respond to the same ease of use and user satisfaction questions after each task without them anchoring their response on the current task to their previous responses. In general, four of the tasks were hypothesized to have a higher degree of cognitive fit with the REA model (because of the greater degrees of localization), while no difference was predicted for the other two tasks. Decision makers typically respond to questions based on salient factors. Since the majority of the tasks were expected to have cognitive fit such that the REA representation most closely matched the task, this should make the cognitive fit effect salient when evaluating the overall satisfaction with the accounting model. Therefore, we expect that if cognitive fit is associated with increased perceived ease of use and user satisfaction, the users of the REA model would perceive their system as easier to use and would be more satisfied with it. This prediction does not indicate that REA users would perceive their system as easier to use and would be more satisfied with it for all tasks. If tasks were designed such that there was a higher degree of localization (and thus, cognitive fit) with the DCA model, then we would predict greater perceived ease of use and user satisfaction with the DCA model.

Covariates

Field independence, as measured by the Group Embedded Figures Test (GEFT) score, was included as a variable since significant differences were found within the novice treatment groups. This construct measures an individual's ability to disembed objects from the larger context in which they occur (Witkin, Oltman, Raskin, & Karp, 1971). Dunn and Grabski (1998) found field independence to be one significant predictor of performance on conceptual modeling design tasks. Gender was also included as a covariate because there was a significant difference in the proportion of female participants relative to male participants within groups.

Results of Statistical Tests

Accuracy, task completion time, and confidence were each analyzed with robust regression, which allows heterogeneous variances and unequal cell sizes. The hypotheses were also analyzed using a repeated measures general linear model and using separate univariate analysis of variance models for each hypothesis, and results were consistent with those presented for robust regression. No interactions between accounting model and experience were significant. All results presented were obtained from the robust regression analysis. Table 2 contains descriptive statistics for each of the four user groups (experienced REA, experienced DCA, novice REA, and novice DCA) for accuracy, completion time, and confidence for each of the six tasks.

Although directional hypotheses are included in this study, all reported statistics are two-tailed because of controversy over the use of one-tailed tests (Lindsay, 1993). Table 3 presents robust regression results for H1, H2, and H3. All three accuracy hypotheses are supported. For H1, a main effect of accounting model was observed ($p < .000$), with REA users completing the strongly localized tasks more accurately than DCA users. No experience effect was observed ($p < .256$); novice users completed those tasks as accurately as experienced users. A marginal effect was also observed for field independence ($p < .057$), with field-independent participants outperforming field-dependent participants. Gender also had a significant effect on accuracy, with females outperforming the males ($p < .023$). For H2, main effects for accounting model ($p < .000$) and for experience ($p < .000$) were observed. REA users completed the moderately localized tasks more accurately than DCA users; experienced users completed those tasks more accurately than did novice users. No effect was observed for field independence ($p < .467$) or gender ($p < .860$). For H3, no effect for accounting model was observed ($p < .342$); DCA users completed the non-localized tasks as accurately as REA users. However, a main effect for experience was observed ($p < .043$); experienced users completed those tasks more accurately than did novice users. No effect was observed for field independence ($p < .149$) or gender ($p < .379$).

Table 4 presents robust regression results for H4, H5, and H6. H4 predicted a main effect for accounting model and no effect for experience. A main effect was observed for accounting model ($p < .049$); however, the effect was in the opposite direction of that predicted. Task completion time was greater for REA users than for DCA users, indicating that DCA users with no localization performed the tasks more quickly than did REA users with strong localization. No experience effect was observed ($p < .955$), nor was any effect observed for field independence ($p < .494$) or gender ($p < .489$). H5 predicted main effects for accounting model and experience. Again, an accounting model effect was observed ($p < .000$) in the opposite direction of that predicted; DCA users with no localization completed the tasks more quickly than did REA users with moderate localization. The prediction of a main effect for experience was not supported; no experience effect was observed ($p <. 743$). Also, no effect was observed for field independence ($p < .989$) or gender ($p < .507$). H6 predicted a main effect for experience and no effect for accounting model. Yet, again, an accounting model effect was observed ($p < .000$). DCA users with no localization completed the tasks more quickly than did REA users with no localization. The prediction of a main effect for experience was marginally significant in the opposite direction of that predicted ($p < .098$); the more experienced participants took longer. No effect was observed for field independence ($p < .117$) or gender ($p < .764$).

Table 5 presents robust regression results for H7, H8, and H9. None of the hypotheses were supported. H7 predicted a main effect for accounting model, with REA users expected to be more confident than DCA users, and no experience effect. No effects were observed for either accounting model ($p < .256$) or

Table 2: Descriptive statistics for accuracy, time, and confidence [Mean (standard deviation) values].

	REA Novice	DCA Novice	REA Experienced	DCA Experienced	Overall Novice	Overall Experienced
Accuracy (Scores out of 100 possible points)						
H1 tasks: Strong localization in REA, Weak/No localization in DCA	82.64 (27.85)	45.15 (31.65)	90.91 (16.86)	46.59 (34.05)	63.39 (34.86)	68.75 (34.66)
Overall REA 83.33 (26.31)						
Overall DCA 45.22 (31.80)						
H2 tasks: Moderate localization in REA, Weak/No localization in DCA	55.87 (23.40)	39.54 (21.55)	81.82 (8.59)	63.64 (21.25)	47.70 (23.84)	72.73 (18.35)
Overall REA 60.62 (23.68)						
Overall DCA 43.96 (23.30)						
H3 tasks: Weak/No localization in REA, Weak/No localization in DCA	33.67 (15.35)	39.80 (18.16)	47.73 (24.89)	44.32 (18.85)	36.73 (17.01)	46.02 (21.61)
Overall REA 36.25 (18.08)						
Overall DCA 40.62 (18.21)						
Task Completion Time (in minutes)						
H1 tasks: Strong localization in REA, Weak/No localization in DCA	4.64 (1.38)	4.27 (1.54)	4.61 (1.72)	5.29 (1.98)	4.78 (1.84)	4.62 (1.52)
Overall REA 5.16 (1.94)						
Overall DCA 4.33 (1.50)						

Table 2: (continued) Descriptive statistics for accuracy, time, and confidence [Mean (standard deviation) values].

	REA Novice	DCA Novice	REA Experienced	DCA Experienced	Overall Novice	Overall Experienced
Task Completion Time (in minutes)						
H2 tasks: Moderate localization in REA, Weak/No localization in DCA	4.32 (1.15)	3.67 (1.54)	4.91 (2.63)	5.39 (2.08)	4.53 (2.02)	4.61 (2.00)
Overall REA 5.30 (2.18)						
Overall DCA 3.79 (1.48)						
H3 tasks: Weak/No localization in REA, Weak/No localization in DCA	4.82 (1.17)	3.86 (1.50)	6.82 (3.36)	6.90 (3.82)	5.38 (3.27)	5.82 (2.66)
Overall REA 6.88 (3.71)						
Overall DCA 4.03 (1.48)						
Confidence (Scores out of 100%)						
H1 tasks: Strong localization in REA, Weak/No localization in DCA	72.00 (19.61)	72.52 (14.87)	73.36 (17.82)	73.35 (16.75)	72.33 (15.76)	72.68 (18.30)
Overall REA 73.35 (16.80)						
Overall DCA 72.42 (15.66)						
H2 tasks: Moderate localization in REA, Weak/No localization in DCA	81.68 (6.71)	76.76 (15.47)	74.82 (16.52)	75.33 (16.60)	76.04 (15.98)	78.25 (12.80)
Overall REA 75.23 (16.44)						
Overall DCA 77.66 (14.35)						
H3 tasks: Weak/No localization in REA, Weak/No localization in DCA	66.73 (17.45)	73.39 (15.48)	63.91 (16.54)	63.14 (20.54)	68.26 (18.81)	65.32 (16.65)
Overall REA 63.28 (19.74)						
Overall DCA 72.17 (15.91)						

Table 3: Robust regression estimates for Hypotheses 1, 2, and 3.
Accuracy = α + β_0Accounting model + β_1Experience Level + β_2Field Independence + β_3Gender + ε

Hypothesis 1: Accuracy with Strong Localization in REA; Weak/None in DCA
Number of observations: 120
$F(4, 115) = 15.93$
Prob > F = .000

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	40.714	5.794	7.027	.000	29.238	52.191
Experience	8.387	7.344	1.142	.256	–6.160	22.933
Field independence	1.524	0.742	1.919	.057	–0.046	2.894
Gender	–13.401	5.811	–2.306	.023	–24.912	–1.890
Constant	31.144	12.148	2.564	.012	7.081	55.207

Prediction: Main effect for accounting model — Result: Main effect for accounting model
Prediction: No effect for experience — Result: No effect for experience

Note: Marginal effect for field independence, effect for gender (females more accurate)

Hypothesis 2: Accuracy with Moderate Localization in REA; Weak/None in DCA
Number of observations = 120
$F(4,115) = 9.38$
Prob > F = .000

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	16.468	4.212	3.910	.000	8.125	24.811
Experience	24.689	5.339	4.624	.000	14.114	35.264
Field independence	0.393	0.539	0.729	.467	–0.675	1.462
Gender	0.744	4.225	0.176	.860	–7.624	9.112
Constant	34.619	8.831	3.920	.000	17.126	52.112

Prediction: Main effect for accounting model — Result: Main effect for accounting model
Prediction: Main effect for experience — Result: Main effect for experience)

Hypothesis 3: Accuracy with Weak/None Localization in REA and in DCA
Number of observations = 120
$F(4,115) = 2.32$
Prob > F = .061

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	–2.978	3.120	–0.954	.342	–9.159	3.203
Experience	8.084	3.955	2.044	.043	0.250	15.919
Field independence	0.580	0.400	1.452	.149	–0.211	1.371
Gender	2.766	3.130	0.884	.379	–3.433	8.966
Constant	27.131	6.543	4.147	.000	14.172	40.091

Prediction: No effect for accounting model — Result: No effect for accounting model
Prediction: Main effect for experience — Result: Main effect for experience

Table 4: Robust regression estimates for Hypotheses 4, 5, and 6.
Task Completion Time = $\alpha + \beta_0$Accounting model + β_1Experience + β_2Field Independence + β_3Gender + ε

Hypothesis 4: Task Completion Time with Strong Localization in REA; Weak/None in DCA
Number of observations: 120
F (4, 115) = 1.56 Prob > F = .189

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	0.674	0.339	1.988	.049	0.002	1.345
Experience	–0.024	0.430	–0.056	.955	–0.875	0.827
Field independence	–0.030	0.043	–0.686	.494	–0.116	–0.056
Gender	–0.236	0.340	–0.695	.489	–0.910	0.437
Constant	4.874	0.711	6.857	.000	3.466	6.282

Prediction: Main effect for accounting model, REA faster — Result: Main effect for accounting model, DCA faster
Prediction: No effect for experience — Result: No effect for experience

Hypothesis 5: Task Completion Time with Moderate Localization in REA; Weak/None in DCA
Number of observations = 120
F (4,115) = 4.10 Prob > F = .004

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	1.242	0.332	3.735	.000	0.583	1.900
Experience	0.138	0.421	0.328	.743	–0.696	0.973
Field independence	–0.001	0.043	–0.013	.989	–0.085	0.084
Gender	–0.222	0.333	–0.665	.507	–0.882	0.439
Constant	3.794	0.697	5.443	.000	2.413	5.175

Prediction: Main effect for accounting model, REA faster — Result: Main effect for accounting model DCA, faster
Prediction: Main effect for experience — Result: No effect for experience

Hypothesis 6: Task Completion Time with Weak/None Localization in REA and in DCA
Number of observations = 120
F (4,115) = 11.14 Prob > F = .000

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	2.241	0.350	6.398	.000	1.547	2.934
Experience	0.740	0.444	1.668	.098	–0.139	1.620
Field independence	0.071	0.045	1.582	.117	–0.018	0.160
Gender	0.106	0.351	0.301	.764	–0.590	0.801
Constant	2.786	0.734	3.794	.000	1.331	4.240

Prediction: No effect for accounting model — Result: Main effect for accounting model, DCA faster
Prediction: Main effect for experience — Result: No effect for experience

Table 5: Robust regression estimates for Hypotheses 7, 8, and 9.
Confidence = α + β_0Accounting model + β_1Experience Level + β_2Field Independence + β_3Gender + ε

Hypothesis 7: Confidence with Strong Localization in REA; Weak/None in DCA
Number of observations: 120
F (4, 115) = 2.58 Prob > F = .041

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	3.263	2.857	1.142	.256	−2.396	8.921
Experience	1.017	3.621	0.281	.779	−6.155	8.190
Field independence	1.156	0.366	3.161	.002	0.432	1.881
Gender	1.489	2.865	0.520	.604	−4.187	7.165
Constant	56.502	5.990	9.433	.000	44.638	68.367

Prediction: Main effect for accounting model Result: No effect for accounting model
Prediction: No effect for experience Result: No effect for experience
Note: Effect for field independence

Hypothesis 8: Confidence with Moderate Localization in REA; Weak/None in DCA
Number of observations = 120
F (4,115) = 1.28 Prob > F = .280

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	−1.311	2.468	−0.531	.596	−6.199	3.577
Experience	0.942	3.128	0.301	.764	−5.254	7.138
Field independence	0.643	0.316	2.035	.044	0.171	1.269
Gender	−0.530	2.475	−0.214	.831	−5.432	4.373
Constant	71.852	5.174	13.887	.000	61.603	82.101

Prediction: Main effect for accounting model Result: No effect for accounting model
Prediction: Main effect for experience Result: No effect for experience
Note: Effect for field independence

Hypothesis 9: Confidence with Weak/None Localization in REA and in DCA
Number of observations = 120
F (4,115) = 3.48 Prob > F = .010

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	−6.720	3.418	−1.966	.052	−13.491	0.052
Experience	−4.099	4.333	−0.946	.346	−12.682	4.484
Field independence	1.083	0.438	2.474	.015	0.216	1.950
Gender	1.470	3.429	0.429	.669	5.322	8.261
Constant	58.440	7.167	8.154	.000	44.243	72.638

Prediction: No effect for accounting model Result: Main effect for accounting model, DCA more confident
Prediction: Main effect for experience Result: No effect for experience
Note: Effect for field independence

experience ($p < .779$) on the tasks for which REA was strongly localized. A main effect was observed for field independence ($p < .002$), with field-independent participants reporting higher confidence levels than field-dependent participants. There was no effect observed for gender ($p < .604$). H8 predicted main effects for both accounting model and experience, with REA users more confident than DCA users and experienced users more confident than novice users on the tasks for which REA was moderately localized. No effects were observed for either accounting model ($p < .596$) or experience ($p < .764$). A main effect was observed for field independence ($p < .044$), with field-independent participants reporting higher confidence levels than field-dependent participants. Again, no effect was observed for gender ($p < .831$). H9 predicted no effect for accounting model and a main effect for experience, with experienced users expected to be more confident than novice users. No effect was observed for experience ($p < .346$); an unexpected main effect was observed for accounting model ($p < .052$), with DCA users more confident than REA users for tasks with no localization. A main effect was observed for field independence ($p < .015$), with field-independent participants reporting higher confidence levels than field-dependent participants. No effect was observed for gender ($p < .669$).

Table 6 presents descriptive statistics and results of robust regression for perceived ease of use. H10 predicted a main effect for accounting model, which served as a surrogate for the degree of cognitive fit, and no effect for experience. No effects were observed for accounting model ($p < .577$), experience ($p < .892$), field independence ($p < .332$), or gender ($p < .529$). Table 7 presents descriptive statistics and results of robust regression for user satisfaction. H11 predicted a main effect for accounting model, which served as a surrogate for the degree of cognitive fit, and no effect for experience. A main effect for accounting model was observed ($p < .000$), with those that had a higher degree of cognitive fit for most of their tasks (REA users) more satisfied than those that had a lower degree of cognitive fit for most of their tasks (DCA users). No main effect for experience was observed ($p < .109$). A main effect for field independence ($p < .014$) was observed, with field-independent individuals more satisfied than field-dependent individuals. No main effect for gender was observed ($p < .683$).

DISCUSSION AND FUTURE RESEARCH DIRECTIONS

David, Dunn, McCarthy, and Poston (1999) developed a framework for AIS research called the Research Pyramid (Figure 4). The premise is that an AIS implementation (the peak of the pyramid) is connected to (the base consisting of) its underlying Symbol set, the Concepts of its designers and users, and to Objects in the organizational reality in which the AIS exists. David, Dunn, and McCarthy (1999) encouraged researchers who are comparing information systems to first do so at the Symbol level to provide a more systematic theoretical basis for comparing specific information system implementations. That is accomplished in this research, which studies the symbol-object-concept face of the research pyramid. We investigate the effects of the REA and DCA symbol sets on the objects accuracy and task completion time, and also on user concepts of confidence, user satisfaction, and perceived ease of use.

Table 6: Descriptive statistics and results of statistical tests for perceived ease of use [Mean (standard deviation) values].

Descriptive Statistics

Perceived Ease of Use (higher is better*)	Higher Degree of Cognitive Fit	Lower Degree of Cognitive Fit
Cumbersome	4.14 (1.30)	4.08 (1.69)
Frustrating	3.97 (1.35)	4.13 (1.74)
Mental effort	4.64 (1.59)	4.12 (1.43)
Understandable	3.78 (1.46)	3.58 (1.38)
Easy to use	4.12 (1.36)	3.98 (1.48)

*A 7-point Likert scale was used, with the anchor of 1 being associated with *strongly agreeing with* cumbersome, frustrating, requiring a lot of mental effort, and *strongly disagreeing* with clear and understandable, or easy to use; and the anchor of 7 being associated with *strongly disagreeing* with cumbersome, frustrating, requiring a lot of mental effort and *strongly agreeing* with clear and understandable, or easy to use.

Robust Regression Results (with Accounting Model as surrogate for Degree of Cognitive Fit)

H10: Perceived Ease of Use = $\alpha + \beta_0$Accounting model + β_1Experience Level + β_2Field Independence + β_3Gender + ε
Number of observations = 119
$F\,(4,114) = 0.50$
Prob > F = .735

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	0.129	0.230	0.559	.577	–0.238	0.585
Experience	0.040	0.291	0.136	.892	–0.536	0.616
Field independence	–0.029	0.029	–0.975	.332	–0.087	0.030
Gender	0.146	0.231	0.632	.529	–0.312	0.604
Constant	4.306	0.481	8.953	.000	3.353	5.259

Prediction: Main effect for accounting model — Result: No effect for accounting model
Prediction: No effect for experience — Result: No effect for experience

Table 7: Descriptive statistics and results of statistical tests for user satisfaction mean (standard deviation) values.

Descriptive Statistics

User Satisfaction (lower is better*)	Higher Degree of Cognitive Fit	Lower Degree of Cognitive Fit
Adequate	2.98 (1.30)	4.27 (1.66)
Efficient	3.22 (1.30)	4.40 (1.62)
Effective	2.98 (1.15)	4.08 (1.42)
Satisfied	3.40 (1.35)	4.17 (1.56)

*A 7-point Likert scale was used, with the anchor of 1 being associated with *adequate, efficient, effective, or satisfied*; and the anchor of 7 being associated with *inadequate, inefficient, ineffective, or dissatisfied.*

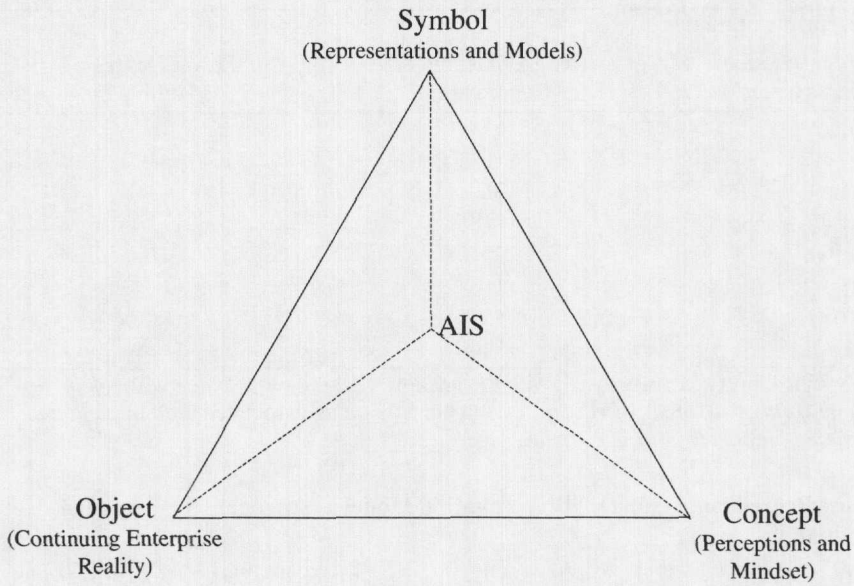
Robust Regression Results (with Accounting Model as surrogate for Degree of Cognitive Fit)

H11: User Satisfaction = $\alpha + \beta_0$Accounting model + β_1Experience Level + β_2Field Independence + β_3Gender + ε
Number of observations = 119
$F(4,114) = 8.01$
Prob > F = .000

	Coefficient	Std. Error	T	$P > \|t\|$	95% Confidence Interval	
Accounting model	–1.270	0.247	–5.143	.000	–1.760	–0.781
Experience	0.503	0.312	1.615	.109	–0.114	1.120
Field independence	–0.079	0.031	–2.505	.014	–0.141	–0.016
Gender	–0.102	0.247	–0.410	.683	–0.592	0.389
Constant	5.376	0.515	10.429	.000	4.355	6.397

Prediction: Main effect for accounting model — Result: Main effect for accounting model
Prediction: No effect for experience — Result: No effect for experience
Note: Effect for field independance

Figure 4: Research pyramid (David, Dunn, McCarthy, & Poston, 1999).



Results of this study for task accuracy support the predictions based on cognitive fit theory and localization, suggesting that localization is an important element of cognitive fit. Without localization and cognitive fit, experienced users outperformed novice users. With a moderate degree of localization provided to REA users (but not to DCA users), the REA users outperformed the DCA users. Experience also mattered, presumably because it helped users to recognize the localization. When the needed information was highly localized for REA users, not only did REA users outperform DCA users, but also the effect of experience was eliminated. A high degree of localization appears to direct novice users' attention well enough that with minimal training they can perform as well as experienced users.

For the results of this study to be meaningful it is important to assess whether REA users actually used the diagrams and tables in completing their solutions, or whether they used the source documents to generate their responses, thereby in essence producing a DCA solution. Of 360 REA participant task responses (6 tasks x 60 REA users), only five responses were completed based only on the source documents. Three of these responses were from one novice user on tasks 3, 5, and 6. This user admitted being confused by the diagrams and would have preferred to see some "numbers to crunch." The other two responses were from novice users on Task 5 (average delivery time for vendors), who were successful in using the E-R diagrams on the other five tasks.

This study used the REA-modeled system as implemented using entity-relationship diagrams and relational tables. While the REA model is designed to be semantic, we do not know how much of the task accuracy findings among the groups are due to the semantics inherent in the REA model or to the diagrammatic conventions and associated attention-directing mechanisms inherent in entity-relationship diagrams and their corresponding relational tables. Future research is needed to determine whether the results generalize to all semantically modeled systems, whether the results are dependent on the graphical representation technique independent of the semantics of the underlying system, or whether both the semantics and representation are critical.

For time and confidence, results were not as predicted based on cognitive fit theory and localization. These results are not entirely surprising, as many extraneous factors contribute to people's confidence and how much time they are willing to spend on a task. These variables have been found in other studies to vary inconsistently with accuracy (see Chervany & Dickson, 1974; Dickson et al., 1977). The results for task completion time may have been caused by the different information loads inherent in the accounting models, as opposed to the degree of localization and cognitive fit. Because the REA model incorporates more semantics and more disaggregated data than does the DCA model, the REA documentation had more data elements to examine. It is likely that the effect of localization was overridden by the effect of the information load. Other cognitive factors or personality traits may affect these variables such that studying cognitive style is not "much ado about nothing," as Huber (1983) claimed. This study reveals that field independence is one such cognitive style that appears to influence confidence, with field-independent individuals exhibiting more confidence on all tasks than did field-dependent individuals. Future research may examine task completion time and confidence with respect to cognitive fit and localization in a more comprehensive fashion, using protocol analysis to gain insight as to factors that would increase predictability. Different types of training and feedback may alter results.

Results for perceived ease of use were also not as predicted. Post-experiment debriefing revealed that most participants, regardless of the model to which they were assigned, thought the number of pieces of paper (accounting model documentation, questionnaire, and sample source documents) with which they had to deal made the tasks cumbersome and frustrating. Computerized administration might help to alleviate some of the apparent information overload participants may have experienced; however, other confounds may be introduced. While the sheer volume of paperwork appears to have daunted all users and affected the results for perceived ease of use, the voluminous paperwork aspect did not appear to affect the results for user satisfaction. Users of the model that provided a higher degree of cognitive fit (i.e., the REA users) were more satisfied with their system than were users of the model that provided a lower degree of cognitive fit (i.e., the DCA users). Field independence also appeared to influence user satisfaction, with field-independent individuals more satisfied with their system than field-dependent individuals.

An open-ended question was included in the experimental questionnaire in order to gain additional self-reported insight as to the users' preferences for the alternative accounting models. Representative responses are provided in Appendix E. Experienced participants greatly preferred the REA format, regardless of which format they used for the tasks. Only one participant stated a preference for DCA information, and that was because he wanted to have specific aggregated numbers typically found in a DCA system. He claimed to prefer REA in general, but also wanted discrete data values. Novice participants were divided as to their format preference. For those who used REA documentation, 25 would rather have had DCA documentation, 17 preferred the REA format that they had, and seven were neutral or gave no response. For those who used DCA documentation, 24 would rather have had REA documentation, 19 preferred the DCA format that they had, and six were neutral or gave no response. The majority of those in both groups that preferred the DCA documentation seemed to want it because they were more experienced with it and were more comfortable with it. Open-ended responses from participants who preferred the REA format provide anecdotal evidence supporting the hypothesis that "localization" is important. The most prevalent responses among respondents were that the REA diagrams helped them to focus on the relationships and enabled them to find the information they were looking for in one place.

Limitations

As with any research there are limitations within this study. The study does not look at the complete model of cognitive fit within the alternative accounting representations, focusing instead on cognitive fit within the REA model. However, the findings that suggest localization enables cognitive fit through attention direction are important and shed new light on how designers should approach the issue of cognitive fit, irrespective of what accounting model (or other non-accounting representation) is employed. The study is also limited by a relatively small number of experienced subjects (22) compared to the novice subjects (98). Nonetheless, for the research to show the levels of significance obtained within the accuracy score provides very strong evidence as to the importance of cognitive fit and localization. The finding of no effect for experience for the most localized tasks (H1) is critical for identifying localization as an important element of cognitive fit. A non-result is always suspect if the power of the test is not adequate (Lindsay, 1993). In this study, it was infeasible to increase the number of experienced participants, and even if it had been feasible, the resulting sample would be nonrepresentative of the underlying population. Because the sample size yielded adequate power to identify experience effects for the moderately localized and non-localized tasks, it is apparent that the experience effects are greater when localization is less. This supports the claim that localization is an important element of cognitive fit.

Another potential limitation is the researchers' grading of the accuracy results; however, a very straightforward grading scheme was applied. In a similar set of tasks using a grader blind to the research questions, interrater reliability between one of the researchers and the independent grader was .89.

Future Directions

We believe research such as the current study, which looks to the basic structure of alternative accounting models, will provide dividends to the accounting and information systems professions and to the users of enterprise information systems. Such research has implications for system design and reporting mechanisms. The current study was not designed to evaluate whether the REA model is superior to the DCA model; rather, the objective was to evaluate effects of different representations on task performance. This research does provide support for the idea that it is important to consider task characteristics when determining what model representation will best support the task. Future research should determine to what extent everyday business decisions require knowledge of relationships that are localized in the REA model versus those that require knowledge that is localized in the DCA model. If more everyday business decisions require knowledge of relationships localized in REA, that could explain why organizations are moving toward REA-type systems (David et al., 1996) and why organizations whose accounting systems possess more REA features perceive that they have a competitive advantage (David, 1996). Our results provide an explanation for why more companies are implementing REA-type systems and for why managers perceive these systems as beneficial. REA systems allow the relationships among the data to be more easily visualized, data are not as limited in dimensionality, and users are more satisfied with these systems since many decisions require knowledge of these relationships. Still, further research may be conducted to determine a structure for flexible interfaces that will allow cognitive fit and localization to be maximized for separate individual tasks.

Perhaps the most important contribution of this paper is that it has demonstrated that we can further the investigation of cognitive fit by extending it to other domains and by investigating what might be happening inside the mental representation box of Figure 2. Many other studies of cognitive fit have treated this construct as a "black box" to be worked around. Future research should continue to unveil the processes decision makers use in developing their mental representations when solving problems and should consider the role of pre-existing mental representations or schemata in that development. Once the mental representation development is more fully understood, systems can be designed to support decision makers for a wider variety of tasks. [Received: October 1, 1999. Accepted: February 16, 2001.]

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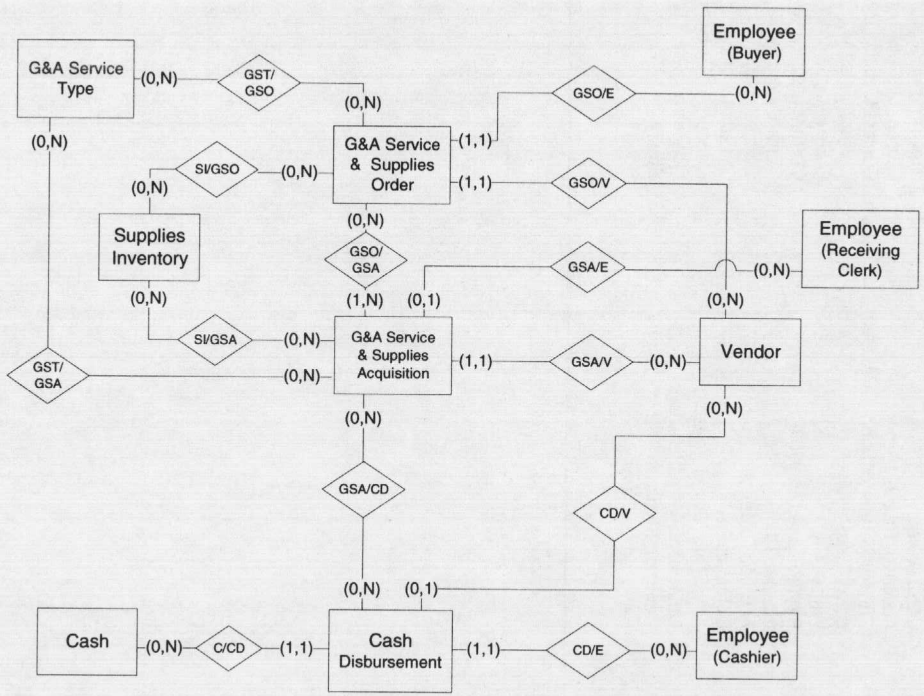
APPENDIX A: REA ACCOUNTING SYSTEM

Sample Entity-Relationship Data Model and Relational Table Intensions



General & Administrative Services and Supplies Acquisition/Payment Business Process

Cash (**Cash Account Number**, Account Type, Bank Name, Cash Account Balance)

Cash Disbursement (**Check Number**, Amount, Date, *Cash Account Number, Payee Number*, Employee Number*)

Employee (**Employee Number**, Name, Address, City, State, Zip Code, Phone, Number of Classification, Payrate, Start Date)

G & A Service Type (**Service Type Number**, Description, Standard Cost)

G & A Service and Supplies Acquisition **G&A Service & Supplies Receipt Number**, Date Received, Receipt Dollar Amount, Discount Rate Offered, Discount Payment Due Date, *Vendor Number, Employee Number*)

G & A Service and Supplies Order **G&A Service & Supplies Order Number**, Order Date, Order Dollar Amount, Service/Delivery Date, *Vendor Number, Employee Number*)

GSA/CD (**G&A Service & Supplies Receipt Number, Check Number**, Dollar Amount Applied)

GSO/GSA (**G&A Service & Supplies Order Number, G&A Service & Supplies Receipt Number**)

GST/GSA (**Service Type Number, G&A Service & Supplies Receipt Number**, Quantity Received, Actual Cost)

GST/GSO (**Service Type Number, G&A Service & Supplies Order Number**, Quantity Ordered)

Supplies Inventory (**Supply Item Number**, Description, Material, Weighted Average Purchase Cost, Purchase Cost, Quantity on Hand)

SI/GSA (**Supply Item Number, G&A Service & Supplies Receipt Number**, Quantity Received, Actual Unit Cost)

SI/GSO (**Supply Item Number, G&A Service & Supplies Order Number**, Quantity Ordered)

Vendor (**Vendor Number**, Name, Address, City, State, Code, Phone, Fax)

*Payee Number can be either Vendor Number, Employee Number, or Customer Number, depending upon the situation.

APPENDIX B

DCA Accounting System Sample Page from Chart of Accounts

Robert Scott Woodwinds

General Ledger Chart of Accounts

Account ID	Account Description	Account Type
10000	Regular Checking Account	Current Asset
10100	Payroll Checking Account	Current Asset
10500	Savings Account	Current Asset
10700	Petty Cash	Current Asset
10800	Cash on Hand	Current Asset
11500	Inventory - Instruments	Current Asset
11515	Inventory - Repair Supplies	Current Asset
11600	Supplies Inventory	Current Asset
12000	Accounts Receivable	Current Asset
12900	Allowance for Doubtful Accounts	Current Asset
14000	Prepaid Expenses	Current Asset
15000	Property, Plant & Equipment	Noncurrent Asset
15100	Accumulated Depreciation	Noncurrent Asset
19000	Other Assets	Noncurrent Asset
20000	Accounts Payable	Current Liability
20100	Current Portion of Long-Term Debt	Current Liability
22000	Sales Tax Payable	Current Liability
23000	Wages Payable	Current Liability
23100	Payroll Taxes Payable	Current Liability
24000	Income Tax Payable	Current Liability
25000	Accrued Expenses	Current Liability
26000	Deferred Revenue	Current Liability
29000	Long Term Notes Payable	Noncurrent Liability
29100	Other Long-term Liabilities	Noncurrent Liability
30000	Common Stock	Equity
39000	Retained Earnings	Equity

APPENDIX C

Sample Document Provided with Both DCA and REA Systems

Robert Scott Woodwinds
The Sweetest Sound in Town
2930 Southern Ave.
Laketown, MI 40826
(517) 223-9900 Fax (517) 223-9990

Merchandise Purchase Order

NO. 900001
This number must appear on all related correspondence, shipping papers, and invoices

To:
Emersmith
6830 Newfound
Kansas City, MO 38916

Ship To:
Robert Scott Woodwinds
2930 Southern Ave.
Laketown, MI 40826

P.O. DATE	REQUISITIONER	SHIP VIA	F.O.B. POINT	TERMS
August 3, 1997	E-04	UPS	destination	1/10, n/30

QTY	UNIT	DESCRIPTION	UNIT PRICE	TOTAL
20	each	F100 - closed hole flute, nickel silver/silver,	231.00	$4,620.00
20	each	F150 - closed hole flute, nickel silver/nickel	225.00	$4,500.00
10	each	F200 - closed hole flute, sterling silver/silver	798.00	$7,980.00
20	each	F300 - open hole flute, nickel silver/silver	261.00	$5,220.00
10	each	F400 - open hole flute, sterling silver/silver	798.00	$7,980.00
12	each	P100 - piccolo, cylindrical bore, nickel silver/silver	239.00	$2,868.00
12	each	P200 - piccolo, conical bore, plastic/silver	274.00	$3,288.00
		SUBTOTAL		$36,456.00
		SHIPPING & HANDLING		0.00
		OTHER		0.00
		TOTAL		$36,456.00

1. Please send two copies of your invoice.
2. Enter this order in accordance with the prices, terms, delivery method, and specifications listed above.
3. Please notify us immediately if you are unable to ship as specified.
4. Send all correspondence to:
   Mr. Dean Harlow
   Robert Scott Woodwinds
   2390 Southern Ave., Laketown, MI 40826
   (517) 223-9900 ; Fax (517) 223-9990

Authorized by   Date

APPENDIX D

Example Model Solution and Grading Criteria

Task 1:

How would you determine **total gross instrument sales** for the period January 1 - April 30?

DCA Model Solution

Get the sale invoices for the period January 1 – April 30. Identify the line items on those invoices that were for instruments and sum them.

DCA Grading Criteria

–25 if wrong dates (or no dates considered)
–25 if use sale order forms instead of sale invoice forms
–25 if does not isolate instrument inventory (from other types of inventory)
–25 if does net sales rather than gross sales

REA Model Solution

Go to the Sale, Inventory, and Sale-Inventory-Line-Item tables. Formulate queries to isolate instruments from other types of inventory and to isolate the dates from January 1 through April 30. For those items, multiply price times quantity sold to get the line item sale amounts and then sum them. Or, could give same solution as DCA model solution using sales invoice source documents.

REA Grading Criteria

–25 if wrong dates (or no dates considered)
–25 if use Sale-Order and Sale-Order-Inventory-Line-Item tables instead of Sale and Sale-Inventory-Line-Item tables (OR if use Sale order forms instead of sale invoice forms if they used the source document solution)
–25 if does not isolate instrument inventory (from other types of inventory)
–25 if does net sales rather than gross sales

Note: Errors were accumulated, so if incorrect dates (or no dates) were considered, and the solution didn't isolate instruments from other inventory items, but everything else was correct, the score would be rated as 50.

APPENDIX E

Open-ended Responses Regarding REA and DCA Format Data

Question asked to DCA users: Would you have preferred to have received REA-based information instead of DCA-based information?

> ***Representative experienced user responses:***
>
> Yes, it gives a clearer picture of how the entire enterprise functions as a unit.
>
> Yes, because it is a lot easier to trace the relationship between objects to determine the needed info.
>
> Yes, I was saying to myself, "If I could look this information up on a relational database with linkages, then I could easily derive the answer instead of manually calculating balances."
>
> ***Representative novice user responses:***
>
> No. I have a much better understanding of chart of accounts because of my accounting background.
>
> Yes! If things are in tables, you have a better sense of what information can be directly linked to what other information, instead of having to look in a million places to find relationships.
>
> Yes, even though I still picture the accounting system as debits/credits, I found the REA gives you a much better understanding of where to find info you need—the flow of info is well represented by the relationships and tables. Everything is there in one diagram and you do not have to go to lots of documents and use a "paper trail."
>
> Possibly, only if there was a clear-cut way to determine answers through the flow, but basically the advantage would have been to have all the relative relationships for a function on one page and not spread out.

Question asked to REA users: Would you have preferred to have received DCA-based information instead of REA-based information?

> ***Representative experienced user responses:***
>
> Heck NO!!!! I like looking at E-R because I see a better overall sense of the transactions and how business works.
>
> No, the E-R diagrams help to picture the flow of information as the transactions occur. It helps to understand what information is captured in what form and where so you can cross-reference.
>
> No—it would be more difficult for me to see the connections and flows between entities.

Representative novice user responses:

No, because using entity-relationship diagrams provides a more comprehensive view of how the individual components of the accounting system interact with one another.

No. The tables and showing what relates to what through the E-R diagram helped visualize a natural flow. For people who think in more visual terms, this makes it easier.

Yes. It is easier for me to see numbers rather than look at diagrams. In the business world people are worried whether or not you can crunch the numbers and be correct rather than if you can follow a confusing diagram or not.

Yes, because right now I have a much better understanding of the debit/credit system. I'm more comfortable with it.

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