Understanding Business Domain Models: The Effect of Recognizing Resource-Event-Agent Conceptual Modeling Structures

Geert Poels, Faculty of Economics and Business Administration, Ghent University, Belgium

ABSTRACT

In this paper, the author investigates the effect on understanding of using business domain models that are constructed with Resource-Event-Agent (REA) modeling patterns. First, the author analyzes REA modeling structures to identify the enabling factors and the mechanisms by means of which users recognize these structures in a conceptual model and description of an information retrieval and interpretation task. Based on this understanding, the author hypothesizes positive effects on model understanding for situations where REA patterns can be recognized in both task and model. An experiment is then conducted to demonstrate a better understanding of models with REA patterns compared to information equivalent models without REA patterns. The results of this experiment indicate that REA patterns can be recognized with minimal prior patterns training and that the use of REA patterns leads to models that are easier to understand for novice model users.

Keywords: *Business Domain Model, Conceptual Modeling, Enterprise Ontology, Modeling Patterns, Model Understanding, Pattern Learning, Pattern Recognition*

INTRODUCTION

The Resource-Event-Agent (REA) enterprise information architecture (Geerts & McCarthy, 2002) is a consensually agreed and theoretically-founded ontology for enterprises that is used as a conceptual modeling framework for enterprise information systems (Dunn, Cherrington, & Hollander, 2005; Hruby, Kiehn, & Scheller, 2006). An ontology is an explicit specification of a conceptualization: the objects, concepts and other entities that are assumed to exist in some area of interest and the relationships that hold among them (Gruber, 1993). Whereas general-purpose conceptual modeling languages (e.g., UML) do not prescribe which objects, relationships, and properties to include in models of some domain, a domain ontology identifies the objects of interest in the domain and offers rules to connect these objects into information structures.

The concepts and structures of the REA ontology are presented as a collection of modeling patterns. Analysts can use the templates that document these patterns as a base solution when creating models. Model users can use the patterns as a reference when reading models

DOI: 10.4018/jdm.2011010104

and trying to understand them. In this study, we examine the structuring capabilities offered by the REA patterns and their effect on the conceptual modeling outcome. Prior research indicates that the use of REA patterns helps in creating more accurate conceptual models (Gerard, 2005), which is important given that information systems are developed based on such models (Olivé, 2007). Conceptual models are, however, also used to help understand phenomena of interest within a domain and to support the communication between users, analysts and developers (Wand & Weber, 2002). The benefits of using patterns for understanding models have not been thoroughly explored. Therefore, we investigate whether recognizing REA conceptual modeling structures improves model understanding.

The second section of the paper provides an introduction to the REA ontology, presents its core structuring principle, i.e., the resource-event-agent pattern, and explains its use in constructing domain models of business processes, thereby defining the type and scope of the conceptual models to which this research applies. The third section reviews prior research and further refines the research question. The fourth section proposes a research model that is based on the premise that users who interact with REA-based conceptual models recognize the resource-event-agent structures. Accordingly, hypotheses are developed based on pattern recognition theories from cognitive psychology. The fifth and sixth sections present the design and conduct of an experiment to test these hypotheses and the analysis of the collected data. Finally, the seventh section presents conclusions, discusses the study limitations and the implications of the research findings, and outlines further research directions.

THE RESOURCE-EVENT-AGENT ONTOLOGY

The REA ontology has been accepted in August 2007 as the international ISO/IEC standard 15944-4, referred to as the Open-edi Business Transaction Ontology (OeBTO). Different reference models and methodologies for designing business services in e-collaboration contexts (e.g., the UN/CEFACT's Modeling Methodology (UMM), the E-Commerce Integration Meta-Framework (ECIMF), the ISO/IEC 14662:1997 reference model for electronic data interchange) use REA as underlying business ontology for grounding the constructs of their modeling formalisms.

Alternative ontologies for the same domain may differ because of the lens through which they look at reality and that determines their domain conceptualization (i.e., the domain concepts that they consider relevant). The basis of REA is the semantic data model for accounting proposed by McCarthy (1982). REA thus focuses heavily on those enterprise concepts that are required to implement accountability and control principles. The conceptualization of an enterprise specified by REA is that of a chain of interconnected transaction cycles that all contribute to the generation of 'value' for the enterprise. Each transaction cycle is an aggregate of (usually two) business processes that effectuate either market exchange transactions or internal conversion operations. An example of the former is the revenues cycle, which integrates sales and collection processes (i.e., the order taking and delivery of a product or service and the collection of the payment make up a 'cycle'). An example of the latter is the production cycle, where the use or consumption of resources like raw materials, labor, machinery, energy, etc. leads to the production of finished goods.

REA describes in a generic way the concepts and relationships that can be identified in the transactional/transformational core of any transaction cycle: the value-affecting events that occur and which are bound by the principle of economic reciprocity (i.e., 'give and take'), the resources whose value is affected by these events and the agents involved in these events. The conceptual modeling structure shown in Figure 1(a) is an ER diagram encoding of this core pattern of concepts and relationships that recurs in every transaction cycle. Figure 1(b) illustrates how this pattern is used to model a retail company's expenditures cycle, which integrates acquisition and payment processes. Economically valuable resources of the company (e.g., *Inventory*, *Cash*) are related to the events occurring in the cycle that cause resource inflows or outflows (e.g., *Purchase*, *Cash Disbursement*). Events that result in resource inflows (e.g., *Purchase*) are related via duality relationships (reflecting economic reciprocity) to events that result in resource outflows (e.g., *Cash Disbursement*). Participation relationships relate events with agents representing the inside parties (e.g., *Purchase Agent*, *Cashier*) and outside parties (e.g., *Vendor*) to the economic exchange that is modeled.

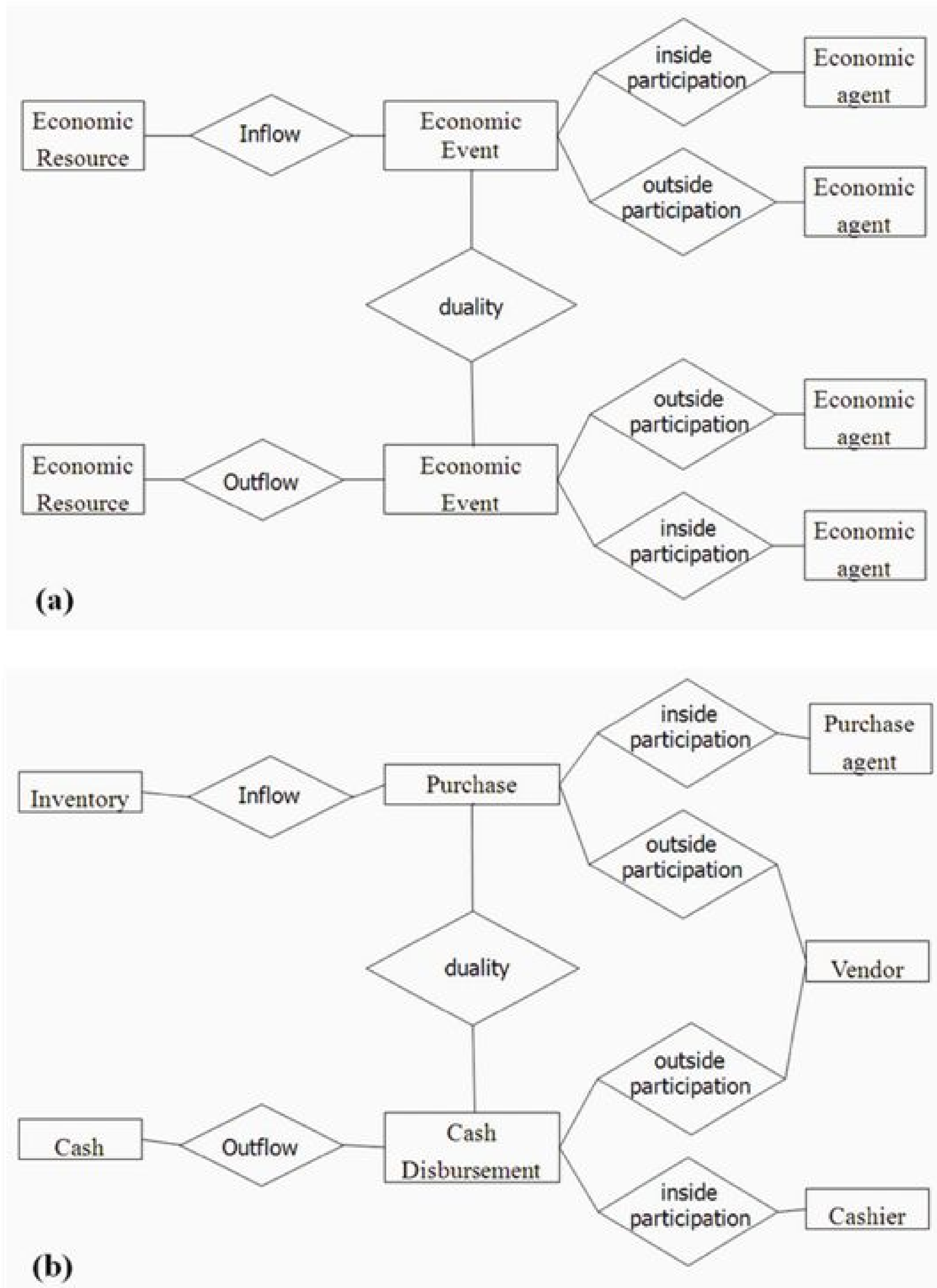
The REA transactional/transformational core pattern shown in Figure 1(a) and additional REA patterns for describing non-core elements of transaction cycles such as claims, policies, schedules, contracts and commitments (see Geerts & McCarthy, 2006; Hruby et al., 2006) constitute a comprehensive and coherent set of patterns for describing enterprise reality. All these patterns are variations of resource-event-agent conceptual modeling structures, meaning constellations of entities in which an agent does something (i.e., performing the event related to the resource) for the benefit of another agent, who does something in return. For instance, in a commitment variation of the core pattern, the events are replaced by commitments, which are promises to execute events in the foreseeable future. In a typification variation, one or more of the resources, events and agents are replaced by an abstract type image (e.g., a particular type of sales like sales with a 10% discount is made to a particular type of customers like 'gold' customers). In an internal conversion context (e.g., production), there typically is only one agent present in the resource-event-agent constellations as there are no outside parties to be represented. This rich set of business patterns has been used as a conceptual modeling framework in the development of various types of enterprise systems, including both accounting information systems (Batra & Sin, 2008; Rosli, Ahmi, & Mohamad, 2009) and non-accounting applications like enterprise planning systems (Church & Smith, 2008), supply chain collaboration systems (Haugen & McCarthy, 2000) and systems supporting production processes (Hruby et al., 2006).

Note that the view of a transaction cycle that is inherent in the REA core pattern (see Figure 1(a)) is a structural view rather than a behavioral view. A structural view on some relevant part of the real world is the view commonly taken in *conceptual data modeling*, which emphasizes the concepts (relevant things and their properties) that constitute that part of the real world (also referred to as the Universe of Discourse (UoD)) and the relationships that provide structure to these concepts. A behavioral view on a transaction cycle and its composing business processes would emphasize more the sequencing of the different process steps or transformations of process states and the (temporal) constraints that determine which execution sequences are valid. To distinguish with the behavioral view, common in *business process and workflow modeling*, we refer to a conceptual model of a transaction cycle according to the structural view as a *domain model* whereas we reserve the term *process model* for the behavioral view.

PRIOR RESEARCH

Transaction cycles are modeled by analysts and transaction cycle information is communicated (via the models) to various kinds of business professionals, including business process workers and managers, and external business consultants. Many of these stakeholders have previously provided input to the modeling process (i.e., during requirements elicitation) and are later asked to validate the models that the analyst has developed based upon this (and possibly other) input (Maes and Poels, 2007). There are other types of business professionals that have not participated in the modeling process, but still must be able to use domain models for retrieving relevant information and correctly interpreting it. Auditors, for instance, check the conformance of business process

Figure 1. ER diagram encodings of resource-event-agent conceptual modeling structures (a) The REA core pattern (b) The REA core pattern applied to the expenditures cycle in a retail company



executions (also called 'cases') by comparing 'audit trails' stored in a log to the domain model. Model-based conformance checking requires an understanding of the model which goes beyond making sense of surface semantics (i.e., the meaning carried over by the labels (names) of the diagram elements, see Siau, Wand, & Benbasat, 1997) as a good comprehension of the semantics of the modeling grammar's constructs is needed to discover the business rules that apply to the process.

The adoption of REA patterns in modeling methodologies and reference models that are the result of international standardization efforts and the possible implication of widespread use, can be seen as measures of 'pragmatic success' (Moody & Shanks, 2003). There is as yet, however, little evidence of the benefits that the REA patterns offer to business professionals that need to work with transaction cycle domain models. According to Antony and Mellarkod (2004), patterns are most useful for non-experts, which they define as functional specialists that contribute towards systems analysis without having much expertise in modeling. Similarly, Batra and Wishart (2004) propose pattern-based modeling as a training approach for novice modelers because they cannot rely on past experience and would therefore benefit most from reusing existing solutions. So what we are particularly interested at are the benefits that REA patterns offer to novice model users.

In scientific studies, students are usually considered as proxies for novice practitioners. Gerard (2005) showed that students possessing knowledge structures consistent with the REA core pattern (as a result of learning) were more accurate in the conceptual design of accounting databases than students with less consistent knowledge structures. The study of Gerard demonstrated the positive effect of the structuring capabilities of the REA core pattern on modeling performance, but did not investigate whether REA patterns also help in understanding models developed by others. Jones, Tsay, and Griggs (2005) compared the task-specific relative strength of five types of diagrams: ER diagrams constructed with REA patterns, process maps, flowcharts, data flow diagrams and UML activity diagrams. An experiment was conducted that showed that students scored best on conceptual data model related comprehension questions with REA pattern-based ER diagrams, whereas for other types of questions (related to data flow, system document flow and sequencing of process activities) they scored better with other diagram types. Although the study of Jones et al. focuses on model understanding, it did not directly compare the use or no use of REA patterns for the same kind of understanding task.

We have previously conducted an experiment (Poels, Maes, Gailly, & Paemeleire, in press) in which the transactional core of two financial transaction cycle variants (i.e., debt financing and equity financing) was modeled a first time using the REA core pattern and a second time without explicit reference to this pattern. We asked students to answer some questions about the debt and equity financing processes modeled giving them either the model with an REA core pattern occurrence or the other model. We measured the time they took to answer the questions and the correctness of their answers. Prior to the experiment, the students were intensively trained in the use of REA patterns (4.5 hours of instruction plus two 1.5 hours practical course sessions).

The results of the experiment indicated that a modeled transaction cycle is more accurately understood if a model that instantiates the REA core pattern is used, however, no statistical significant difference in the time taken to perform the experimental task was observed. As noted in (Poels et al., in press), the absence of a demonstrable efficiency effect might be the result of a too low statistical power level for the hypotheses tests, because of the small scale of our experiment (only 30 participants). Another explanation offered is that we should have used also perception-based measures (e.g., ease of use, user information satisfaction) to investigate whether the correct answers to the questions asked can be inferred easier and quicker from the information provided by the model with the REA pattern occurrence.

Although the results of this first study indicate that an experimental investigation of the benefits that REA patterns offer to novice model users is feasible, a larger scale study that employs a wider variety of measures (both performance- and perception-based) is needed to provide a more conclusive answer to the following research question:

Is an ER diagram that is used as a conceptual model of a transaction cycle better understood by novice business users if it contains REA pattern occurrences?

It is important to note that an ER diagram showing transaction cycle related information can be developed without using the REA patterns. Such an ER diagram may also contain other pattern occurrences than REA patterns. Batra (2005) provides a synthesis of conceptual data modeling patterns, some of which can be used to model transactions. These patterns describe conceptual modeling structures that frequently occur in real-world conceptual data models. From a scientific point of view it could be worthwhile to compare the effect on model understanding of using the ontology-based REA patterns with that of using alternative, empirically-derived transaction patterns. Instead, the research question formulated here is motivated by a pragmatic consideration. Given that several international standards for modeling collaborative business processes (i.e., ISO/IEC 15944, ISO/IEC 14662:1997, UMM and ECIMF) have based their modeling methodologies and reference models on REA patterns, an answer to the research question would help practitioners deciding whether or not to adopt an REA-based modeling standard. We believe that such a decision is a more realistic practical motive for our research than the question which collection of patterns to use, even if from a scientific standpoint such a study may provide valuable insights into the relative merits of ontology-derived and empirically-derived patterns.

RESEARCH MODEL

To derive testable hypotheses from our research question we looked at theories that explain the mental process called pattern recognition. Pattern recognition research in psychology has identified enabling factors and the cognitive and perceptual mechanisms that trigger pattern recognition. Batra (2005) and Antony and Mellarkod (2004) have suggested a number of theories used in the fields of analogical reasoning and similarity finding that might be useful for explaining how conceptual data modeling patterns are recognized. An example is the Structure-Mapping Theory (Gentner & Medina, 1998), which proposes three mechanisms (i.e., literal similarity, abstraction and analogy) by means of which pattern recognition works (Antony & Mellarkod, 2004).

Considering enabling factors for pattern recognition, the REA core pattern and its representation as a template (i.e., the generic pattern, as in Figure 1(a), or as an ER diagram fragment, see the pattern occurrence in Figure 1(b)) exhibit two specific features that facilitate pattern recognition processes and mechanisms. The first feature is called *localization* (Dunn & Grabski, 2001) and relates to the ontological structuring of information elements offered by a modeling pattern. Localization means that a modeling pattern acts as a conceptual topological structure in which information elements can easily be localized because of their predetermined position relative to each other. This feature holds also for the other patterns that are part of the REA ontology.

The second feature, not shared by the other REA patterns, is *secondary notation* (Petre, 1995) which refers to the visual structuring capabilities offered by a fixed format modeling template, which ensures that the REA core pattern's topological structure of information elements becomes a spatial topological structure (instead of a purely conceptual topological structure). The fixed format of the REA core pattern template (see Figure 1(a)) is formed by a diagram layout where the entities representing resources, events and agents are placed in respectively a left, middle, and right column of the diagram. By instantiating the REA core pattern template of Figure 1(a), the position of information elements in a model is not only fixed relative to each other, but also fixed relative to the page containing the model (i.e., a fixed absolute positioning). The use of spatial relations and location in the plane when drawing system design diagrams has been investigated by Nickerson, Corter, Tversky, Zahner, and Rho (2008) who show that such 'affordances of the page' help making designs clearer. For instance, the physical separation of clusters facilitates grouping and abstraction processes that reduce memory load by reducing the number of units to keep in mind. The grouping of resources, events and agents in separate diagram columns can be seen as an example of such a physical clustering process.

Localization, and for the REA core pattern also secondary notation, ensure that the REA patterns behave like patterns according to the notion assumed in the pattern recognition theories discussed, i.e., as recurring structures of information elements that can be recognized because of their unique clues for discrimination. For instance, if a user familiar with the REA patterns sees an ER diagram with entities arranged in three columns and she can interpret one of the entities in the middle column as an event, then she can quickly follow one or a few links to the left, right or to other entities in the middle column and check whether the entities found match her expectations (i.e., being resources, agents or other events). If so, she will likely conclude that the diagram is built around an REA core pattern occurrence, i.e., she has recognized the pattern. After this recognition, the other elements of the pattern can easily be found (because the user knows where to look for them) and interpreted in terms of REA ontological semantics.

With respect to pattern recognition in the description of an information retrieval and interpretation task, it is possible that users familiar with the REA patterns will structure their mental representation of the required information according to these patterns for tasks that fit the purpose of REA pattern-based modeling. A task requiring the retrieval and interpretation of transaction cycle information from a business domain model would fit that purpose. For instance, if somebody (e.g., an internal auditor) needs to find out which function in the enterprise is responsible for accepting deliveries of goods, and this person is familiar with the REA patterns, then she is likely to interpret the question as "which internal agent participates in accept delivery of goods events?".

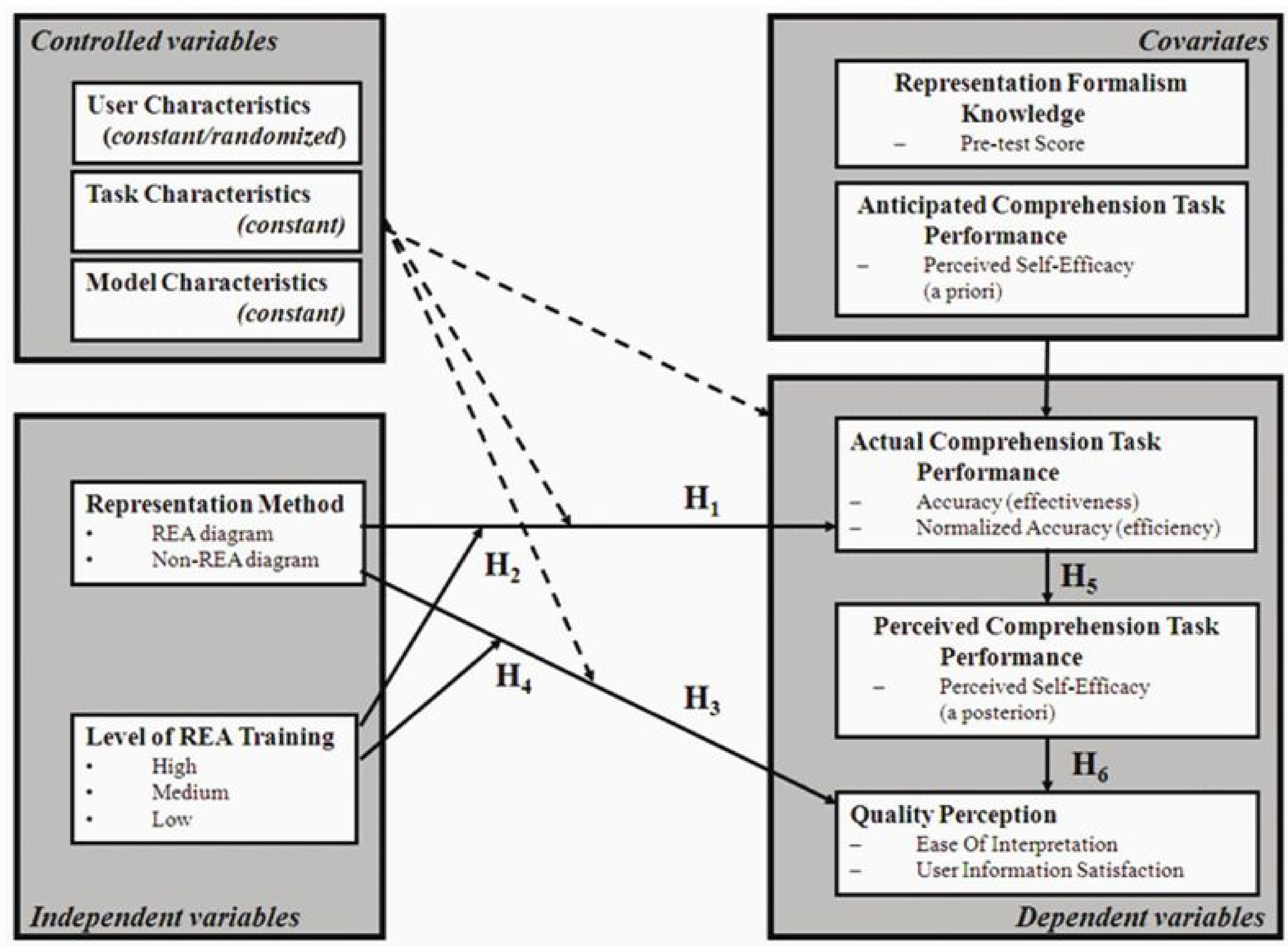
The research question and the reviewed pattern recognition theories suggest a research model for this study. The research model shown in Figure 2 includes the relevant constructs and relationships that are used as variables and hypotheses in this study. Note that the model is already operationalized for the experiment conducted. However, the discussion of the operational details like treatments and measures is deferred to the next section.

The main factor under investigation is the *Representation Method* for domain models of transaction cycles and its effect on the user understanding of the models. Given that for the conceptual modeling of a single transaction cycle, the use of the REA pattern-based modeling approach results in an ER diagram (hereafter called an *REA diagram*) with REA pattern occurrences that can be recognized by users familiar with the REA patterns, we hypothesize that such a diagram is better understood than an ER diagram that was not obtained using the REA approach (hereafter called a *Non-REA diagram*). The argumentation for this hypothesis is that users confronted with a task requiring transaction cycle information to be retrieved from an ER diagram (i.e., a model comprehension task), will create a mental representation in which the required information is structured according to the familiar REA patterns (i.e., pattern recognition in the task). If the ER diagram is an REA diagram, then it is likely that the users will recognize these structures of information in the model. Therefore we hypothesize that *Actual Comprehension Task Performance* will be *effective* (i.e., successful retrieval and interpretation of the required information) and *efficient* (i.e., with low cognitive effort involved, thus fast). If on the other hand the ER diagram is a Non-REA diagram, then no REA patterns can be recognized in the model. Consequently, a less effective and efficient task performance is expected.

Hypothesis 1: The use of an REA diagram instead of a Non-REA diagram to represent a conceptual model of a transaction cycle will have a positive effect on comprehension task performance (in terms of effectiveness and efficiency).

The pattern recognition theories reviewed stress that to recognize a pattern it must be present in one's memory. This presence is achieved through learning, which is a mental process that can involve instruction, training and experience. Without this learning, pattern recognition cannot occur, so to investigate our research question, we need to consider both processes. Hypothesis 1 assumes the presence of REA patterns in memory so that the REA pattern occurrences in the REA diagram can be

Figure 2. Research model



recognized, but abstracts from the strength of their presence. The probability that patterns are recognized when a user sees an REA diagram increases with the strength of their presence in memory, which we assume to be related to the amount of learning. As experience is hard to control, we focus on learning as a result of education. Therefore, the *Level of REA Training* is introduced as a variable in the research model and an interaction effect with *Representation Method* is hypothesized. The stronger the presence of REA patterns in memory, the higher the probability that pattern recognition in the model takes place, but only for models that contain REA pattern occurrences, as in models without REA pattern occurrences there are no REA patterns to recognize. So we hypothesize that the level of REA training has a positive effect on comprehension task performance for REA diagrams only.

Hypothesis 2: The positive effect that the use of an REA diagram has on comprehension task performance will increase with the level of REA training. The comprehension task performance when using a Non-REA diagram is not affected by the level of REA training.

The usability of conceptual modeling techniques should not only be measured in terms of objective performance, but also in terms of users' attitudes towards the techniques, the tasks performed using the techniques, and their own performance (Topi & Ramesh, 2002). It is probable that users that can recognize REA patterns will be less satisfied when they have to solve the problem posed by the task using a diagram that does not contain REA pattern occurrences. It is also likely that such users will perceive non-REA diagrams as more difficult to use than REA diagrams. In line with our previous hypotheses, we hypothesize that in situations where pattern recognition in the model is likely to occur, users will have a more favorable perception of ease of use and will be more satisfied. Similar to the hypothesized effect on performance, we formulate two hypotheses related to *Quality Perception*. Hypothesis 3 assumes that REA patterns have been learned but abstracts from the amount of learning. On the other hand, Hypothesis 4 takes the *Level of REA Training* into account and states an interaction effect with *Representation Method*.

Hypothesis 3: The use of an REA diagram instead of a Non-REA diagram to represent a conceptual model of a transaction cycle will have a positive effect on the user's perception of model quality (in terms of ease of use and satisfaction).

Hypothesis 4: The positive effect that the use of an REA diagram has on the user's quality perception will increase with the level of REA training. Model quality perception when using a Non-REA diagram is not affected by the level of REA training.

Model quality perceptions are also contingent on the comprehension task performance. Moody (2002) theorized in his Method Evaluation Model that quality perceptions are caused by the actual effectiveness and efficiency of task performance. It is thus possible that the effect of *Representation Method* on *Quality Perception* (as well as the interaction effect with training) is only indirect, via *Actual Comprehension Task Performance*. This would mean that quality perception is high because the comprehension task was performed effectively and efficiently, which we hypothesized to be the case when using REA diagrams (Hypothesis 1) and especially when REA diagrams are used by users with a high level of REA training (Hypothesis 2). To test this alternative explanation, a link from comprehension task performance to quality perception is introduced in the research model. If users have not received feedback on their task performance (as in the experiment conducted; see the next section), this link must be implemented using another user attitude, *Perceived Comprehension Task Performance* (Goodhue & Thompson, 1995). This variable captures the user's perception of task performance. This perception might be different from the actual outcome (unknown to the user). Burton-Jones and Meso (2008) showed that measures of perceived understanding are less effective in assessing real understanding than measures of actual understanding. Nevertheless, we cannot preclude that when users perform bad (or good), they are aware of this (even if not knowing the actual results) and perceive their task performance accordingly.

Hypothesis 5: Actual comprehension task performance is related to perceived comprehension task performance.

Hypothesis 6: Perceived comprehension task performance is related to perceived model quality (in terms of ease of use and satisfaction).

The research model shows a number of other variables that will be controlled in the experiment to increase the internal validity of the study. They include *User Characteristics* other than level of REA training (e.g., demographic and personality characteristics, domain familiarity, working experience), *Task Characteristics* (e.g., task fit with purpose of REA ontology, task difficulty, nature of the task), and *Model* (or *Representation*) *Characteristics* other than representation method (e.g., size and complexity of the diagram, modeling language and notational system used). For instance, if users are intimately familiar with the domain that is modeled, they might perform the comprehension task based on their previous knowledge of the domain instead of the information conveyed by the diagram (Burton-Jones & Weber, 1999). So, the domain familiarity of the study participants must be controlled by presenting them with models of not too familiar domains and by ensuring that, if still some level of domain familiarity is expected, that this level is the same for all treatment groups.

Two further variables will be controlled in the study by including them as covariates in the data analysis. The first variable is *Representation Formalism Knowledge*, a user characteristic. Knowing how information elements and structures are represented using the constructs of the ER Model is a prerequisite for being able to derive domain information from ER diagrams. Research has shown that data modeling experience and knowledge of modeling techniques impact model comprehension (Kim & March, 1995; Parsons, 2003; Khatri, Vessey, Ramesh, Clay, & Park, 2006). As we cannot preclude that higher levels of REA training are associated with better knowledge of the ER formalism, this variable must be controlled and its effect cancelled out using appropriate data analysis techniques. The second variable, also a user characteristic, is the user's belief in her ability to successfully perform the task. This belief has been described using the concept of perceived self-efficacy (Bandura, 1997; Ajzen, 2002), which has been shown to be related to actual task performance outcomes (Smith, Change, & Moores, 2003). As users having received more REA training might have higher levels of self-efficacy, the impact of this variable on actual comprehension task performance can be controlled by using it as a covariate. To distinguish this variable from *Actual Comprehension Task Performance* (i.e., observed task performance) and *Perceived Comprehension Task Performance* (i.e., user perception of the task performance), the self-efficacy of users *before* the task is referred to as *Anticipated Comprehension Task Performance*.

RESEARCH METHOD

Topi and Ramesh (2002) assume in their generic research model for human factors related research in conceptual modeling, complex moderating effects of the user and task variables on the relationship between representation formalism/method and user performance and attitudes. Parsons and Cole (2005) state, however, that because of the relative small amount of theory-based experimental work in the area of conceptual modeling, a focus on simple, theoretically causal relationships involving one or a few independent variables is needed. To demonstrate the basic causal effects of representation mechanisms and control other variables, a laboratory experiment is preferred because the complexity and lack of control in real settings would make such study nearly impossible (Parsons, 2005; Siau & Rossi, in press). We therefore designed a 2 × 3 between-subjects experiment. The two levels of the first factor, *Representation Method*, are the experimental treatments (i.e., REA diagram and Non-REA diagram). The second factor, *Level of REA Training*, has three levels (i.e., Low, Medium, and High). This design allows assessing the representation method's impact on task performance and user quality perceptions (Hypotheses 1 and 3) as well as the interaction effect of representation method and level of REA training (Hypotheses 2 and 4).

Participants and Allocation to Experimental Groups

The participants were a group of business students enrolled in a junior-level Management Information Systems (MIS) course at a European university. This group of students approximates a representative sample of the target population, i.e., business professionals that are novices with respect to the use of transaction cycle domain models. The advantage of student participants instead of using 'real' novice model users is that controlling the *User Characteristics* variable becomes easier. In particular, a student's familiarity with the REA patterns is relatively easy to assess, compared to people working in business, which might have diverse (educational) backgrounds. The learning of REA patterns can be explicit (i.e., education) or implicit (e.g., experience), but implicit learning is much harder to observe and measure. The students participating in the experiment formed a more homogeneous group with respect to their educational background and working experience, which would not be the case if business professionals were used, even if only novices were selected to participate. With this students group, the possibility of REA ontology patterns present in memory because of working experience can practically be ruled out, which facilitates the operationalization of the *Level of REA Training* independent variable and the control over a possible confound posed by working experience.

During the course module that focused on conceptual data modeling, students were first taught the constructs and grammatical rules of the ER model. The notation used for ER diagrams was based on UML. Apart from studying the ER model, students were shown examples of and learned to read ER diagrams of various domains (e.g., university personnel management, hospital operations). The subsequent course module exercises required students to retrieve and interpret information conveyed by ER diagrams (e.g., answering questions like 'Can a research assistant be a PhD student?' and 'Can a patient be treated by a doctor from another hospital?').

After the course sessions on ER modeling, the students were given a 1-hour lecture on business domain reference models in which they were introduced to the main patterns of the REA enterprise ontology. Four reference models (order-to-cash, purchase-to-pay, payroll, and production) were explained in this lecture. Following the lecture, students could engage in one or two parts of practical course work similar to the previous ER diagram exercises, but now performed on REA diagrams (i.e., conceptual models instantiating the REA ontology-based reference models seen in class). Students had to register for these optional parts of the course, so the identity of the students participating was known to us. These two 1.5 hours exercise sessions were run in small groups (maximum 6 students), each under the supervision of a teaching assistant. Although attendance was strictly controlled and student participation was intense, the teaching assistant did not actually test the learning outcome at the end of each session. Hence we can only assume that the additional exposure to REA conceptual modeling structures strengthened their presence in memory for those students attending the exercise sessions.

Apart from the lecture on reference models and the subsequent practical course work, no other lecture, practice session or course assignment was devoted to REA patterns. We thus observe three levels of REA training differing in their extent of exposure to the REA patterns:

Low: students not participating in the practical course work on REA modeling;
Medium: students participating in only the first part of REA practice;
High: students participating in both the first and second part.

An assumption underlying the construction of the *Level of REA Training* variable is that the differences in the extent of exposure to REA patterns between the Low, Medium and High levels reflect differences in the amount of learning and thus differences in the strength of presence of REA patterns in memory. Note that apart from differences in the amount of exposure, the additional exposure to REA patterns was also more recent (at the time of the experiment) for the Medium and High groups, which may also strengthen their presence in memory.

The experiment was conducted after finishing the conceptual modeling module of the course. A total of 124 students from the course participated in the experiment, of which 22 were classified as Low, 69 as Medium, and 33 as High with respect to their level of REA training. This uneven distribution of participants across the three levels of REA training implies that this factor is a measured, rather than a manipulated variable. Both participation in the REA exercises and in the experiment was voluntary making it impossible to ensure that each level of REA training was equally well covered. On the other hand, the allocation of the participants to the REA diagram and Non-REA diagram treatments was random, so representation method is a manipulated variable. The randomization of the *User Characteristics* variable per treatment controls for possible differential influences on the dependent variables. Table 1 summarizes the experimental design and participant allocation.

Instrumentation

The REA and Non-REA diagrams used as experimental objects are included in the Appendix (Figures 7 and 8). These diagrams had to be representations of the same domain to control the possible confounding effects of domain complexity and familiarity. The example chosen for the experiment was the hiring, employing and paying of external consulting services which is a cycle of transactions that the experiment participants had not looked at during the course (neither during the optional exercises with REA diagrams).

Another requirement for the experimental objects is their informational equivalence (Siau, 2004). Otherwise, differences in information content may confound attempts to measure the impact of the independent variables on the dependent variables (Parsons & Cole, 2005). To ensure the informational equivalence of the REA and Non-REA diagrams, the different treatment diagrams were constructed by applying diagram transformations that are information-preserving, meaning that they do not change the information content of the diagrams. Two kinds of transformations were applied:

(1) Changing the diagram layout by repositioning diagram elements: this transformation changes the look but not the information content of the diagram. Hence, informational equivalence is ensured by definition.

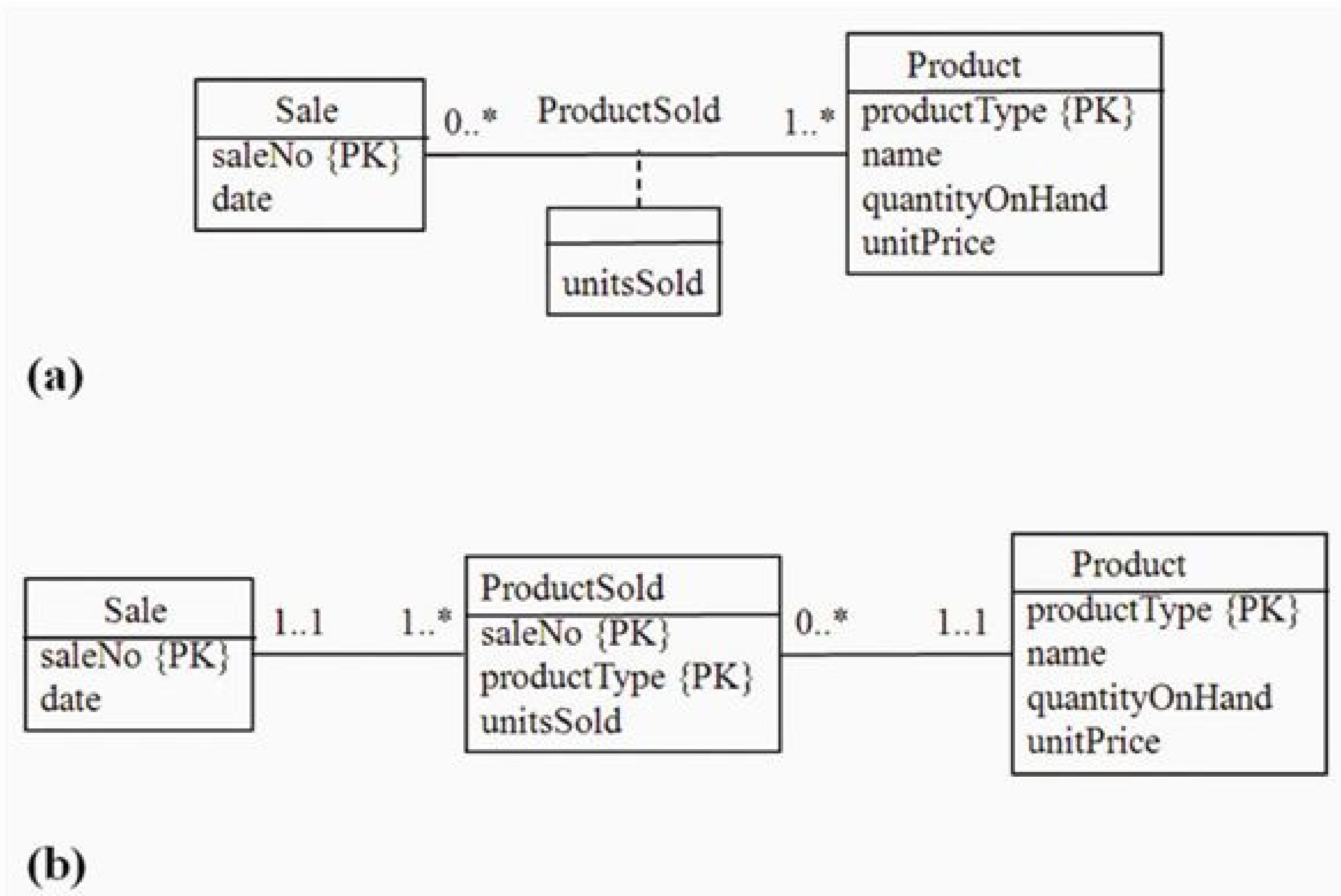
(2) Direct representation or objectification of many-to-many relationships: A many-to-many relationship between two entities can be directly represented by means of an UML association or can be objectified, i.e., replaced by a new entity and two one-to-many relationships between this new entity and the existing entities. The informational equivalence between both types of representation has been demonstrated (Dedene & Snoeck, 1995; Wand, Storey, & Weber, 1999). In the conceptual data modeling module of the MIS course from which our study participants were drawn, both types of relationship representation were taught. Figure 3 provides an example of objectification. The many-to-many relationship *ProductSold* in Figure 3(a) is replaced in Figure 3(b) by the entity *ProductSold*, the one-to-many relationship between *Sale* and *ProductSold* and the one-to-many relationship between *Product* and *ProductSold*. The primary key of *ProductSold* is a concatenation of the primary keys of *Sale* and *Product*, which avoids the existence of multiple links between a particular sale and a particular product.

Related to the second transformation (objectification), we also considered modeling events as relationships instead of entities (Allen & March, 2006). If events are modeled as relationships then their attributes will be contained in an UML association class attached to the UML association that represents the relationship. The number of entities related to the event determines the degree of the relationship that

Table 1. Experimental design and participant allocation

Number of participants in each condition		**Representation Method**		Total
		Non-REA diagram	*REA diagram*	
Level of REA Training	*Low*	11	11	22
	Medium	34	35	69
	High	17	16	33
Total		62	62	124

Figure 3. Objectification (a) The relationship ProductSold between Sale and Product represented as an UML association (b) The relationship ProductSold represented as an UML class



would be used to model the event. Although the transformation of events modeled as entities into events modeled as relationships seems an obvious choice, it does not result in informationally equivalent models as often a particular resource and a particular agent can be linked more than once via events (of the same type). Modeling events as relationships would not allow showing these multiple links.

To create the Non-REA diagram, objectification was applied to the *IsPaymentFor* duality relationship in the REA diagram (Figure 4). The explicit modeling of the duality of 'give' and 'take' events is the most distinctive structuring idea of the REA ontology. Also the *Orders* relationship was objectified (Figure 5). The explicit modeling of relationships between commitments and resources is another essential modeling structure, widely used in REA ontology-based reference models, including those shown in the one hour lecture on business domain reference models given to experimental participants. Objectifying the duality and reservation relationships helps in hiding the conceptual topological structure that REA-trained users expect to find when looking at a diagrammatic representation of a business process. For instance, if a REA-trained user interprets the *Get Consulting Services* entity as an event, then she knows that its dual event (*Pay Consulting Services*) can be found by navigating a single (duality) relationship. The introduction of a connecting entity *Consulting Services Paid* in the Non-REA diagram reduces this localization and thus makes the matching of diagram fragments to the pattern templates stored in memory more difficult.

By repositioning diagram elements we strived for a layout design for the Non-REA diagram that is different from the REA modeling conventions. In the layout for the Non-REA diagram that we created (Figure 8 in the Appendix), the entity representing the outside party (*Consulting Firm*) was selected as the central diagram element. Further, the sequence of event occurrences (*Order Consulting Services – Get Consulting Services – Pay Consulting Services*) was positioned around this central element (in counterclockwise order) such that there is a logical path that can be followed when reading the diagram. Hence, the logic of the Non-REA diagram layout can equally well be justified as that of the REA diagram. The main difference with the REA diagram is that the usual three-column R-E-A arrangement is no longer present. The physical repositioning of diagram elements removes this secondary notation clue and thus hinders the analogy mapping process.

Experimental Tasks

There were two tasks: a pre-test for measuring knowledge of the ER representation formalism (a covariate in the study) and the experimental task proper, which was a comprehension task.

The pre-test (included in the Appendix) was the same for all participants and comprised 15 questions either literally taken from or derived from a similar test presented in Parsons and Cole (2005). The purpose of this test is to assess the user's understanding of the semantics conveyed by ER diagram structural elements (i.e., entities, relationships and structural constraints). The test evaluates how well users can apply their knowledge of the domain-independent semantics of the ER model constructs when interpreting ER diagrams.

The experimental task proper was performed using the diagram given (either the REA or the Non-REA diagram). The task consisted of answering 15 questions about the transaction cycle that deals with the engagement of external consulting services as it was represented in the diagram. As the diagram was the only information source available for answering the questions, participants were 'forced' to make an effort to understand the diagram. The diagram comprehension questions (also included in the Appendix) required the participants to retrieve and interpret transaction cycle information, in particular to derive or verify the policies that govern the transaction cycle.

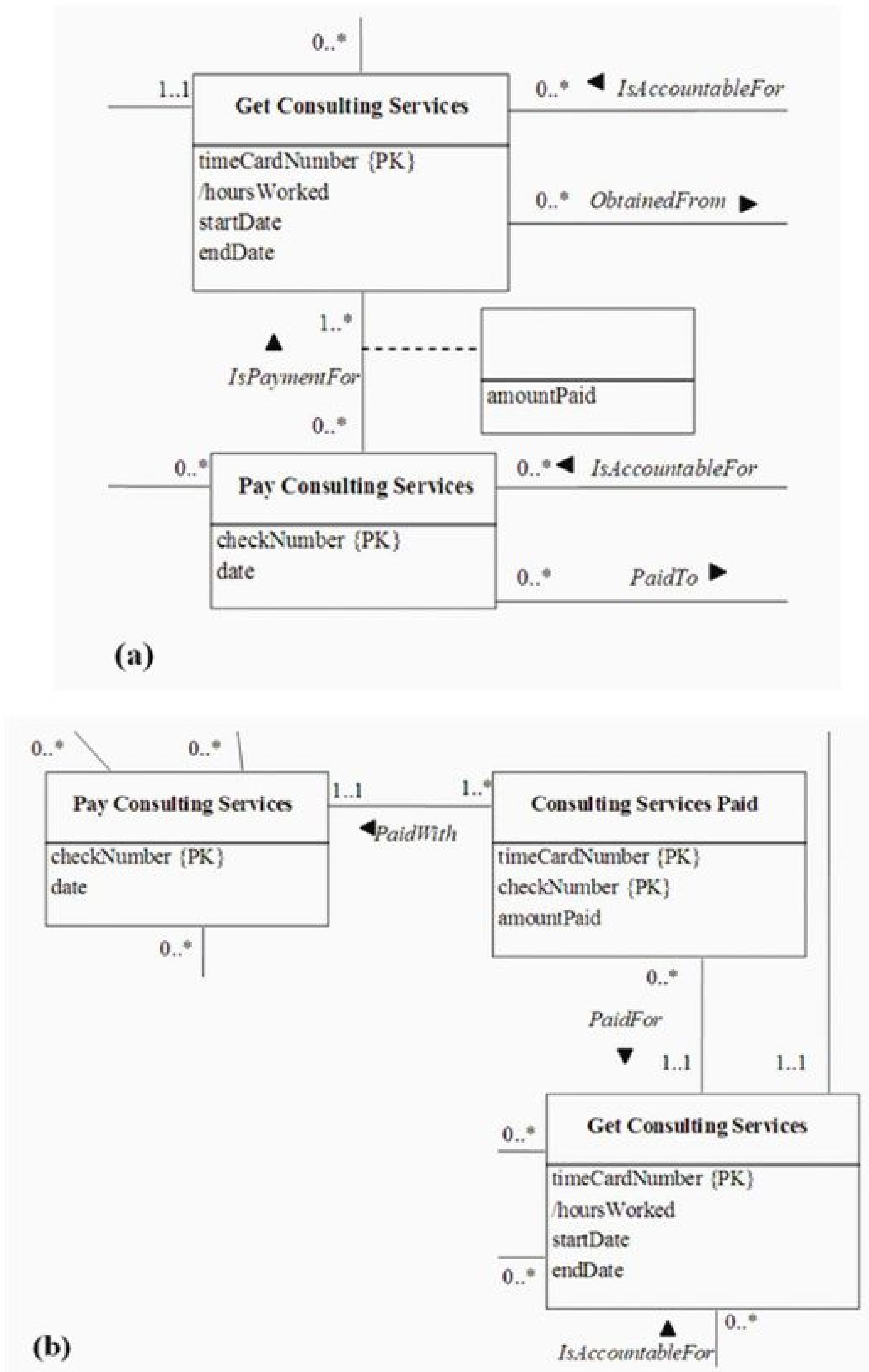
To answer the questions, participants had to search the diagram for relevant pieces of information (entities and/or attributes), identify the links between these pieces of information (relationships), and interpret the structural constraints that are specified for these links (participation and cardinality constraints) in terms of the business rules set for hiring, employing and paying external consultants. For instance, to answer question 12 ("Can it be that we do not know which clerk is accountable for a given timecard?") participants need to find the entity *Clerk*, the entity *Get Consulting Services* (via the attribute *timeCardNumber*) and the relationship *IsAccountableFor* between these entities. Next the structural constraints on this relationship must be correctly interpreted such that it is understood that there can be no timecard without there being a clerk accountable for it (i.e., mandatory participation of *Get Consulting Services* in *IsAccountableFor*)).

The questions were adapted from similar questionnaires for assessing and comparing the user comprehension of conceptual models that are produced via alternative conceptual modeling techniques (Bodart, Patel, Sim, & Weber, 2001; Burton-Jones & Weber, 2003; Gemino & Wand, 2005). Comprehension questions of the kind we used are the conventional instrument for measuring how well users understand the information that is conveyed by a conceptual model (Gemino & Wand, 2003; Parsons & Cole, 2005).

In order to make sure that the comprehension questions were not biased towards the REA treatment two design controls were implemented. First, the questions were phrased such that no specific REA terminology was used. So the questions did not literally reference concepts such as event, resource, agent, inflow, outflow, participation, duality, and commitment. The presence of these terms could facilitate the triggering of the literal similarity mechanism such that the required information elements that correspond to these concepts are easier to localize in the REA diagram. For instance, phrasing question 12 as "Can it be that we do not know which clerk agent participates in a get consulting services event?" would provide literal clues for REA-trained users where to look for the answer in an REA diagram.

Second, the informational equivalence of the REA and Non-REA diagram ensures that the correct answer to a question can be found using either diagram. Therefore exactly the same questions could be used for both treat-

Figure 4. Objectifying the IsPaymentFor duality relationship (a) fragment of the REA diagram (confer Figure 7) (b) fragment of the non-REA diagram (confer Figure 8)

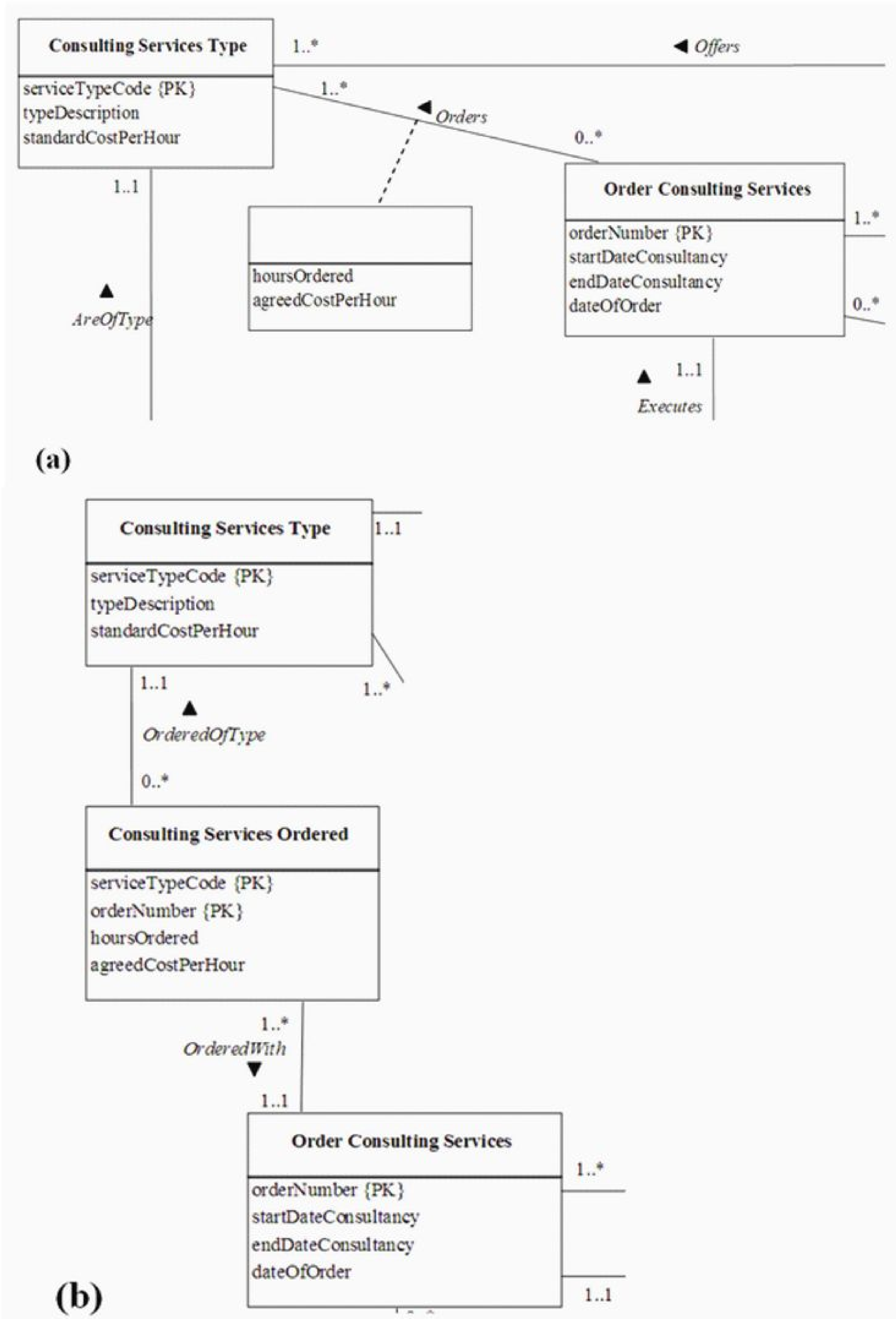


ments. Informational equivalence does not imply computational equivalence (Siau, 2004), so even if the correct answer *can* be found using either diagram, it does not automatically follow that the correct answer *will* be found (as quickly and easily) using either diagram. By using the same questions for both treatments we control the *Task Characteristics* variable of the research model. The feasibility of answering each of the questions using either diagram was controlled a-priori by the experimenters.

Measures

The covariate *Representation Formalism Knowledge* was measured by the score on the ER formalism pre-test, calculated as the number of pre-test questions correctly answered. *Anticipated Comprehension Task Performance*, the second covariate, was measured via the Perceived Self-Efficacy (PSE) construct. Since PSE is a task-specific construct, its measurement should also be specific to the particular task

Figure 5. Objectifying the Orders reservation relationship (a) fragment of the REA diagram (confer Figure 7) (b) fragment of the non-REA diagram (confer Figure 8)



under investigation (Bandura, 1997). Previous studies employing PSE were mainly concerned with end-user training and basic computer use rather than information systems development tasks. The PSE measure that we developed is based on the PSE measures used in (Ryan, Bordoloi, & Harrison, 2000; Smith et al., 2003) who investigated PSE in a conceptual modeling research context. The measure is referred to as the PSE_before measure, to distinguish it from the PSE_after measure used for *Perceived Comprehension Task Performance* (confer infra). The items of the PSE_before instrument (included in the Appendix) were administered as a pre-experiment questionnaire.

To measure the effectiveness dimension of *Actual Comprehension Task Performance*, comprehension task accuracy was defined as the number of correctly answered comprehension questions. To measure the efficiency of a diagram in communicating domain information to the user, the Normalized Accuracy measure of Bodart et al. (2001) was used. This measure relates a participant's comprehension task accuracy and task completion time. It is calculated as the number of comprehension questions correctly answered divided by the time taken to complete the comprehension task. Other research (see Genero, Poels, & Piattini, 2008; Parsons, 2003) has used task completion time as an alternative, but completion time measures efficiency reliably only if a certain level of accuracy is reached. In practice, a better comprehension may be compromised by a faster comprehension, and vice versa (Bodart et al., 2001). Normalized accuracy should in this context be understood as a productivity measure, i.e., relating an output variable (accuracy of comprehension) to an input variable (comprehension time).

The *Perceived Comprehension Task Performance* was again measured via the PSE items that we defined, but now formulated in the past tense, and referred to as the PSE_after items (see the Appendix). We believed that, when formulated in the past tense, the items would capture the participants' perception of how well they accomplished the task (on condition that the instrument is administered directly after the experimental task).

Finally, the *Quality Perception* construct, and more specifically, the dependent variables Perceived Ease Of Interpretation (PEOI) and User Information Satisfaction (UIS), were assessed using existing measures that have been validated before in empirical studies on conceptual modeling (Dunn & Grabski, 2001; Gemino & Wand, 2005). The items of the PEOI and UIS instruments can also be found in the Appendix. Together with the PSE_after items they constituted the post-experiment questionnaire.

Operational Procedures

The experiment was organized as a class room exercise. The students were informed beforehand that this exercise was also part of a research study and that additional data in the form of questionnaires would be collected. However, no information was given with respect to the research questions that would be tested (to avoid experimenter bias). Participation was strictly voluntary and no course credits could be earned.

Students were motivated to participate in two ways. First, we promised feedback on their performance, suggesting that a similar exercise could be part of the final course exam. Second, four prizes (iPod Shuffles and Nanos) were distributed to the best performers. Students were informed that the ranking would be determined based on their scores, and, in case of equal scores, on the time spent. To avoid a ceiling effect, no time limit was set.

When participants entered the class room, they were randomly distributed by a teaching assistant across the two treatment groups and assigned a seat such that neighbors belonged to different treatment groups. The exercise/experiment consisted of four parts, to be executed in the order given (only when a previous part was handed in, the participant received the next part):

(1) A sheet containing instructions, asking for the participant's name and student number, and containing the pre-experiment questionnaire with the PSE_before items;

(2) The ER formalism pre-test (15 questions);
(3) The comprehension task (15 questions) – at this moment the REA or Non-REA diagram was given to the participant and the time was written down by a teaching assistant; when finished, the participant wrote down the time again (projected on a screen in front of the class room) and notified the teaching assistant (who collected the solutions and checked the times);
(4) The post-experiment questionnaire with the PSE_after items, and the PEOI and UIS items (intermingled on the questionnaire).

DATA ANALYSIS AND INTERPRETATION

Effect on Comprehension Task Performance (Hypotheses 1-2)

First, the hypothesized effect of *Representation Method* on *Comprehension Task Performance* (Hypothesis 1) and the interaction effect with *Level of REA Training* (Hypothesis 2) are tested. Table 2 presents descriptive statistics for comprehension task Accuracy and Normalized Accuracy.

To test the hypotheses, a MANCOVA was performed with Accuracy and Normalized Accuracy as dependent variables, *Representation Method* and *Level of REA Training* as factors, *Representation Method* × *Level of REA Training* as interaction term, and Pre-test Score (measuring *Representation Formalism Knowledge*) and a priori Perceived Self-Efficacy (PSE_before; measuring *Anticipated Comprehension Task Performance*) as covariates. Results are shown in Table 3.

The model with Normalized Accuracy as dependent variable is not significant ($p = 0.325$), so no effect on the efficiency of comprehension task performance can be demonstrated. The model with Accuracy as dependent variable is significant ($p = 0.001$) with significant effects observed for the factors *Representation Method* ($p = 0.003$) and *Level of REA Training* ($p = 0.019$), and the covariate Pre-test Score ($p = 0.007$). No significant effects are found for the interaction term ($p = 0.447$) and the covariate PSE_before ($p = 0.250$).

These results provide partial support for Hypothesis 1: REA diagram users scored significantly higher on the comprehension task than Non-REA diagram users (mean Accuracy score of 11.4 for REA (maximum = 15) versus 10.5 for Non-REA with an observed effect size of 0.39 which represents a medium effect size). In other words, the use of REA patterns in the ER diagram had a positive effect on the effectiveness dimension of user comprehension, meaning that REA diagram users showed a more accurate understanding of the business process as modeled.

The absence of an interaction effect between *Representation Method* and *Level of REA Training* means that there is no support for Hypothesis 2, which stated that comprehension task performance when using an REA diagram increases with the level of REA training, whereas comprehension task performance when using a Non-REA diagram would not be affected by the level of REA training. The profile plot in Figure 6 shows that the *Level of REA Training* affects the accuracy of user comprehension, but that this effect is not essentially different for REA and Non-REA diagram users. Post-hoc tests showed a significant difference in Accuracy score between the Low and High training groups ($p = 0.005$) and a marginally significant difference between the Low and Medium groups ($p = 0.058$). Hence, regardless of the representation method used for the ER diagram, users with medium to high levels of REA training gave more correct answers to the comprehension questions than users with a low level of REA training. The increase in accuracy when going from Low over Medium to High levels of REA training is stronger for Non-REA diagram users than for REA diagram users, and accordingly the differences between the REA and Non-REA treatments are not as big as at the Low level of training. It seems that additional REA training is beneficial for understanding REA diagrams, but that the benefits gained in terms of better understanding need to be balanced against the cost of this additional training.

Table 2. Descriptive statistics of Comprehension Task Performance for each experimental condition

	Representation Method	Level of REA Training	Mean	Std. Deviation	N
Accuracy	REA	Low	11.0909	2.16585	11
		Medium	11.2857	1.84026	35
		High	11.9375	1.38894	16
		Total	11.4194	1.79752	62
	Non-REA	Low	9.3636	1.96330	11
		Medium	10.5000	1.74512	34
		High	11.1765	1.38000	17
		Total	10.4839	1.77174	62
	Total	Low	10.2273	2.20242	22
		Medium	10.8986	1.82422	69
		High	11.5455	1.41622	33
		Total	10.9516	1.83841	124
Normalized Accuracy	REA	Low	0.93645	0.383526	11
		Medium	0.76267	0.285855	35
		High	0.79778	0.264155	16
		Total	0.80256	0.301610	62
	Non-REA	Low	0.62115	0.248058	22
		Medium	0.74898	0.301293	69
		High	0.76573	0.238924	33
		Total	0.73089	0.277240	124
	Total	Low	0.77880	0.354095	22
		Medium	0.75593	0.291475	69
		High	0.78127	0.248023	33
		Total	0.76673	0.290736	124

As expected, participants that demonstrated a better understanding of ER modeling concepts (*Representation Formalism Knowledge*, measured in the pre-test), were also more accurate in the subsequent comprehension task. This result is not surprising given that knowledge of the representation formalism is a prerequisite for the correct interpretation of models. The inclusion of *Representation Formalism Knowledge* as a covariate in the research model allows controlling this user characteristic and eliminating its effect when testing the main and interaction effects. As a Post-Hoc test we verified that the mean Pre-test Score was not different between the 2 × 3 experimental groups. An ANOVA revealed no significant differences, which is especially relevant for the 'measured' *Level of REA Training* variable. The lack of correlation between the Pre-test Score and the *Level of REA Training* confirms that the additional exposure to REA for the medium and high *Level of REA Training* groups did not deepen the students' ER formalism knowledge.

The performance on the comprehension task anticipated by the participants (as measured by PSE_before; Cronbach's alpha 0.848) was not related to their actual performance. In fact, this variable was not significantly correlated to any of the other variables used in the MANCOVA, indicating that the self-efficacy of the participants *prior to the experiment* was effectively controlled in the experiment and that this user characteristic plays no role of interest in the study.

Effect on Quality Perception (Hypotheses 3-6)

The post-experiment questionnaire included the items of the Perceived Ease Of Interpretation (PEOI), User Information Satisfaction (UIS), and Perceived Self-Efficacy (in the a posteriori

Table 3. MANCOVA comprehension task performance

Source	Dependent Variable	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	Accuracy Normalized Accuracy	80.020[a] 0.686[b]	7 7	11.431 0.098	3.950 1.170	0.001 0.325	0.192 0.066
Intercept	Accuracy Normalized Accuracy	57.791 0.333	1 1	57.791 0.333	19.970 3.983	<0.001 0.048	0.147 0.033
Pre-test score	Accuracy Normalized Accuracy	22.144 0.004	1 1	22.144 0.004	7.652 0.045	0.007 0.833	0.062 <0.001
PSE_before	Accuracy Normalized Accuracy	3.876 0.108	1 1	3.876 0.108	1.339 1.287	0.250 0.259	0.011 0.011
Representation Method	Accuracy Normalized Accuracy	27.268 0.367	1 1	27.268 0.367	9.422 4.387	0.003 0.038	0.075 0.036
Level of REA Training	Accuracy Normalized Accuracy	23.890 0.007	2 2	11.945 0.004	4.128 0.044	0.019 0.957	0.066 0.001
Representation Method X level of REA Training	Accuracy Normalized Accuracy	4.692 0.367	2 2	2.346 0.183	0.811 2.192	0.447 0.116	0.014 0.036
Error	Accuracy Normalized Accuracy	335.690 9.711	116 116	2.894 0.084			
Total	Accuracy Normalized Accuracy	15288.000 83.293	124 124				
Corrected Total	Accuracy Normalized Accuracy	415.710 10.397	123 123				

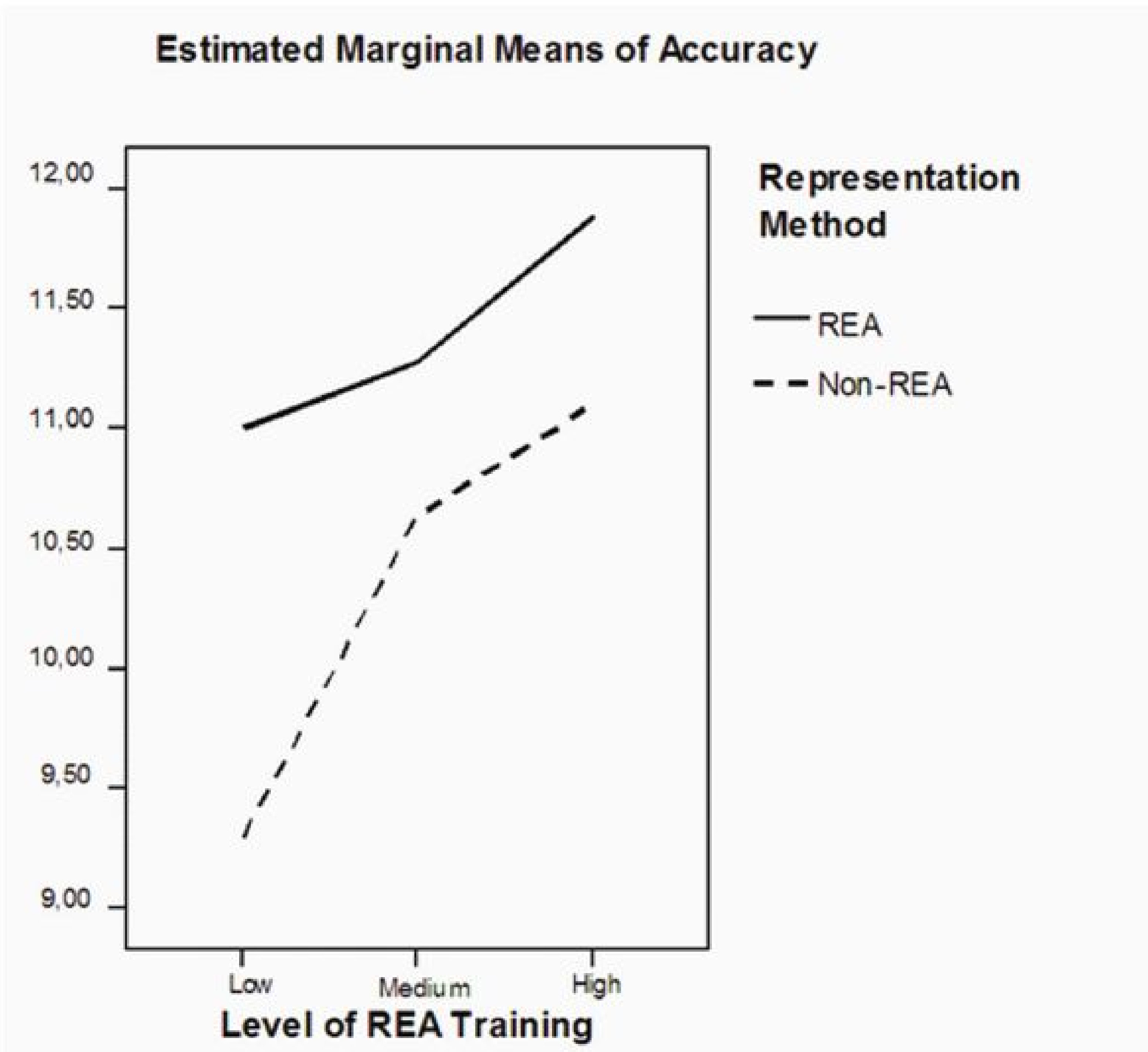
a. R Squared =0.192 (Adjusted R Squared=0.144)
b. R Squared =0.066 (Adjusted R Squared =0.010)

version, i.e., PSE_after) measures. Whereas PEOI and UIS are existing measures, PSE_after was newly developed for this study. Therefore, and because all three measures capture perceptions about the use of a conceptual model, a reliability and validity analysis was conducted before testing hypotheses 3 – 6.

Initial Cronbach alpha's were 0.722 for PEOI, 0.826 for UIS, and 0.837 for PSE_after. A factor analysis revealed a problem of low discriminant validity for PEOI item 2 ("Using the conceptual schema was seldom frustrating"), so it was not further considered in the rest of the analysis (i.e., the average PEOI scores were calculated without item 2 scores). The removal of PEOI item 2 increased the Cronbach alpha value for PEOI to 0.791, well above the usual reliability threshold value of 0.70. It was further verified that all items of the new PSE_after measure loaded on a single factor, separate from the PEOI and UIS items.

Next, the hypothesized effect of *Representation Method* on *Quality Perception* (Hypothesis 3) and the interaction effect with

Figure 6. Profile plot accuracy



Level of REA Training (Hypothesis 4) were tested. Table 4 presents descriptive statistics for the perception-based variables PEOI and UIS.

The hypotheses were tested by means of a MANCOVA with PEOI and UIS as dependent variables, *Representation Method* and *Level of REA Training* as factors, *Representation Method* × *Level of REA Training* as interaction term, and a posteriori Perceived Self-Efficacy (PSE_after; measuring *Perceived Comprehension Task Performance*) as covariate. The inclusion of PSE_after as a covariate in the analysis is legitimate as covariates can be (continuous) independent variables in their own right (and given that the other independent variables are categorical). The MANCOVA is thus also used to test the hypothesized relationship between *Perceived Comprehension Task Performance* and *Quality Perception* (Hypothesis 6). The results of the MANCOVA are shown in Table 5.

Both models are significant ($p < 0.001$) with a strongly significant effect observed for PSE_after ($p < 0.001$). The MANCOVA results allow accepting Hypothesis 6 stating that the perception of model quality is related to the perception of comprehension task performance.

Empirical evidence of an effect of *Representation Method* on the quality perceptions (Hypothesis 3) is found in the marginally significant effect that this factor has on PEOI ($p = 0.083$). The inclusion of PSE_after as a covariate in the analysis adjusts the means on the PEOI dependent variable to what it would be if all participants scored identically on PSE_after. So, independent of the effect that PSE_after has on PEOI, using an REA diagram instead of a non-REA diagram has a (slight) positive effect on the user's perceived ease of interpreting the model. This effect found provides weak support for Hypothesis 3. As an effect of *Representation Method* on UIS was not shown ($p = 0.305$), the support for Hypothesis 3 is only partial (i.e., only with respect to PEOI).

Apart from the effect of PSE_after on PEOI and UIS and the effect of *Representation*

Method on PEOI, no other effects of the factors and interaction term on the dependent variables are observed. There is no support for Hypothesis 4 as no interaction effect is present in the data collected. Contrary to what we observed for Accuracy, the Level of REA Training has no direct effect on model quality perception.

To test the hypothesized relationship between actual and perceived task performance (Hypothesis 5), two separate regressions were performed (given the significant correlation between the Accuracy and Normalized Accuracy scores). ANOVA results showed significant correlations between Accuracy and PSE_after ($p = 0.015$) and between Normalized Accuracy and PSE_after ($p < 0.001$), leading to the acceptance of Hypothesis 5. Hence, the hypothesized relationship between actual and perceived comprehension task performance was corroborated.

Given that both hypotheses 5 and 6 were accepted, it is plausible that diagram users that performed well on the comprehension task (both in terms of effectiveness and efficiency) developed a favorable perception of their task performance (i.e., they realized that they correctly understood the diagram without spending much effort) and accordingly perceived the diagram as easy to interpret, and were satisfied with the information provided for answering the comprehension questions. Note that by itself, the acceptance of hypotheses 5 and 6 does not imply that REA diagram users perceived the diagram as easier to interpret and were more satisfied with it than Non-REA diagram users. Also Non-REA diagram users with good comprehension task performance (both actual and perceived) are likely to form high-quality perceptions of the diagram. On the other hand, as demonstrated in the previous sub-section, comprehension task performance measured as accuracy was higher with REA diagram users. Furthermore, the partial support found for Hypothesis 3 evidences a direct effect of REA diagram use on the perceived ease of interpretation.

DISCUSSION AND CONCLUSION

In our experiment, REA diagram users were more accurate than Non-REA diagram users in solving the model comprehension task. This observed effect is only an effectiveness effect as no significant differences were found when relating the number of correct answers to the time taken to perform the task. This result confirms the findings of our previous study (Poels et al., in press), which suffered from low statistical power because of its small scale. A difference with this previous study is that the experiment also showed that the actual comprehension task performance was related to perceptual and satisfaction outcomes (perceived performance, ease of use and user satisfaction). These relationships indicate that participants who performed well on the comprehension task also perceived the diagram as easy to interpret and were satisfied with using the diagram for retrieving the information required by the task. However, apart from these relationships, also a (weak) direct effect of representation method (REA or Non-REA diagram) on perceived ease of interpretation was found. Because comprehension task performance was used as a covariate in the statistical data analysis, the observed effect on quality perception stands besides the performance effect that was demonstrated. Hence, our study provides further evidence of the computational nonequivalence of informational equivalent REA and Non-REA diagrams. Based on the results we can conclude that users that have learned the REA patterns perceive diagrams with REA pattern occurrences as easier to interpret than diagrams without, so their perception is that they can draw easier and quicker inferences from the information present in REA diagrams. Given that all the participants received minimal REA education (though some of them were trained more intensively) and were to some extent familiar with the REA patterns' semantics and representation conventions, the more accurate model understanding and the more favorable perception of ease of understanding with REA

Table 4. Descriptive statistics of quality perception for each experimental condition

	Representation Method	Level of REA Training	Mean	Std. Deviation	N
UIS	REA	Low	5.022	0.5528	11
		Medium	4.335	1.1261	35
		High	4.843	0.9911	16
		Total	4.588	1.0422	62
	Non-REA	Low	4.454	0.8277	11
		Medium	4.360	0.9578	34
		High	4.485	0.9456	17
		Total	4.411	0.9200	62
	Total	Low	4.738	0.7459	22
		Medium	4.347	1.0389	69
		High	4.659	0.9698	33
		Total	4.500	0.9830	124
PEOI	REA	Low	4.545	1.2496	11
		Medium	3.619	1.0668	35
		High	4.041	1.2224	16
		Total	3.892	1.1762	62
	Non-REA	Low	3.242	1.0337	11
		Medium	3.607	1.1502	34
		High	3.843	1.2862	17
		Total	3.607	1.1680	62
	Total	Low	3.893	1.3027	22
		Medium	3.613	1.1005	69
		High	3.939	1.2401	33
		Total	3.750	1.1761	124

diagrams provide evidence of pattern recognition taking place.

It was also noted that participants who received additional training in REA were significantly more accurate in the comprehension task than participants with minimal REA training. But this effect was observed for both REA and Non-REA diagram users, so there is no direct evidence that pattern recognition is stronger or more frequent when users are (assumingly) more familiar with the patterns. It is possible that the extra REA training (in the form of exercises) provided to (some of) the students helped them understand the conceptual model better because of the additional and more recent exposure to solving comprehension tasks of the type required in the experiment. The higher or more recent experience with model comprehension tasks might explain the positive effect of REA training on comprehension accuracy, regardless of the representation method used. Our study thus demonstrates the intuitive relationship between training and performance. Training novice model users in understanding conceptual data models helps them to better understand models. However, based on the results of this experiment, we cannot conclude that novice model users should be intensively trained in the use of REA conceptual modeling structures as maybe training with other kinds of conceptual data models would also improve model understanding.

The results of this study have implications for practice. Our experiment with business students indicates that transaction cycle domain models constructed with REA patterns are better understood than models without. This finding is significant given that resource-event-agent structures frequently occur in conceptual data models of enterprise information systems.

Table 5. MANCOVA quality perception

Source	Dependent Variable	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	UIS PEOI	34.65[a] 64.14[b]	6 6	5.775 10.69	8.023 11.80	<0.001 <0.001	0.291 0.377
Intercept	UIS PEOI	29.91 3.479	1 1	29.91 3.479	41.56 3.841	<0.001 0.052	0.262 0.032
PSE_after	UIS PEOI	28.12 51.55	1 1	28.12 51.55	39.06 56.90	<0.001 <0.001	0.250 0.327
Representation Method	UIS PEOI	0.765 2.776	1 1	0.765 2.776	1.063 3.064	0.305 0.083	0.009 0.026
Level of REA Training	UIS PEOI	3.144 1.971	2 2	1.572 0.985	2.183 1.088	0.117 0.340	0.036 0.018
Representation Method x Level of REA Training	UIS PEOI	0.866 0.450	2 2	0.433 0.225	0.601 0.248	0.550 0.781	0.010 0.004
Error	UIS PEOI	84.22 105.99	117 117	0.720 0.906			
Total	UIS PEOI	2629.87 1913.88	124 124				
Corrected Total	UIS PEOI	118.87 170.13	123 123				

a. R Squared=0.291 (Adjusted R Squared =0.255)
b. R Squared=0.377 (Adjusted R Squared =0.345)

For instance, McCarthy (2004) estimates that 60% of the ER diagrams that make up SAP's ERP reference model consist of resource-event-agent structures. Also O'Leary (2004) found SAP data models to be consistent with resource-event-agent structures and concludes that REA is robust in its ability to represent SAP data models. The practical significance of our finding is further strengthened by the use of the REA patterns in various international standards, methodologies and reference models for modeling collaborative business processes (i.e., ISO/IEC 15944, ISO/IEC 14662:1997, UMM and ECIMF).

Our study also shows that the use of REA patterns can be beneficial even at a limited level of REA education. Whereas in the previous study (Poels et al., in press) an effect on the accuracy of model understanding was shown for users extensively trained in REA patterns (4.5 hours of instruction plus 3 hours of training in working with REA diagrams), we now observe differential effects for participants that received between 1 and 4 hours of REA education. For the group of students that only received a 1 hour lecture on business domain reference models constructed using REA patterns, the improvement in mean Accuracy score by using an REA diagram instead of a Non-REA diagram is 18.45%. While it is hard to evaluate whether this improvement is practically meaningful (in terms of improved communication between analysts and business professionals), the cost of one hour of instruction is probably not excessive given the improvement in model understanding that can be expected. The use of REA conceptual modeling structures will of course also require training for the analysts and thus present an additional cost, but on the other hand, as indicated by the study of Gerard (2005), also positive effects on modeling performance may result from the use of REA patterns.

At higher levels of training, model understanding further improves. Companies that adopt the use of REA conceptual modeling structures may expect further increases in model understanding when they provide more REA training to their novice model users. However, based on our study alone it is difficult to tell whether more intensive levels of REA training really pay off as this also depends on the cost of training. Compared to the improvement of 18.45% in mean Accuracy score by using an REA diagram instead of a Non-REA diagram (at a limited level of REA education), the marginal gains in the accuracy in understanding REA diagrams observed at higher levels of training seem limited. In the experiment, the improvements in mean Accuracy score for REA diagram users go up with 1.76% and 5.78% when moving from the Low to Medium and from the Medium to the High levels of training. The statistically significant difference in Accuracy score between the Low and High training groups is mainly due to the improvement observed for the Non-REA diagram users, where the mean score has increased with 19.36%.

Apart from evaluating REA patterns-based conceptual modeling, our study also contributes to the research on conceptual (data) modeling patterns. The focus of the research to date is on performance effects of pattern use by (novice) designers or analysts and the pattern matching (or retrieval) techniques that are used in this process (Batra & Wishart, 2004; Irwin, 2002; Purao, Storey, & Hahn, 2003). Whereas previous research has emphasized pattern recognition in the information requirements put forward by a modeling task, our study also pays attention to pattern recognition in the conceptual model itself and provides first indications that the use of patterns can also be beneficial for model users. Although our study identified two features of REA patterns, localization and secondary notation, as enabling factors for pattern recognition, the data collected does not allow isolating their effects and studying how these pattern characteristics trigger pattern recognition mechanisms like analogy, abstraction or literal similarity. Further explorative research is required to generalize the findings of this study to other modeling patterns that exhibit the same characteristics. Such research could use verbal techniques of protocol analysis to get deeper insights into the mental process of pattern recognition, i.e., to find out how patterns really help in understanding conceptual models.

Most of the conceptual modeling patterns research done focuses on patterns that have been empirically derived (i.e., through discovery of recurrent structures in real models). Our study suggests that patterns derived from an ontology may be especially useful for helping users to better understand models. Because of their level of comprehensiveness, abstraction and structuredness, enterprise ontologies are valuable educational instruments for teaching the conceptual modeling of enterprise systems, something which is clearly demonstrated for the REA ontology (Gailly, Laurier, & Poels, 2008). Patterns derived from ontologies all share the same level of abstraction and granularity, and their occurrences can easily be integrated because the patterns are positioned in an overarching structure. So, another implication of our study results is that it could be worthwhile further investigating ontology-derived patterns and not focusing solely on empirically-derived patterns. It logically follows that, as suggested earlier in the paper, a comparative study of ontology-derived and empirically-derived patterns may provide valuable insights into the relative merits of both types of patterns.

The limitations of this study are the degree to which the results can be generalized and the degree of confidence we can have in causation conclusions from a single laboratory experiment. Task characteristics were held constant by having the same task to be performed under all treatments. This task was realistic in the sense that it reflects typical use of business domain models by business professionals. Moreover, the task was tailored to the purpose of the type of models that can be constructed with REA patterns as it involved the retrieval and interpretation of transaction cycle information that is relevant from an accountability and control perspective. A consequence of this intended task-technology fit is that we do not and cannot demonstrate better performance for other purposes than those for which REA patterns-based conceptual modeling is intended. Apart from the use or no use of REA pattern occurrences, all other model and representational characteristics were held constant. Further, only one case was used in the experiment. These experimental design choices helped increasing internal validity by controlling variables such as informational equivalence, domain familiarity, model size, and notational system used. With respect to domain familiarity, Khatri et al. (2006) showed that domain knowledge has little effect on comprehension task performance if the task involves extracting knowledge directly represented in the model, which was the case in our study. Nevertheless, future research may wish to replicate this study using other examples of transaction cycles, with different model sizes and/or other modeling notations to confirm our results and hence increase the generalizability of the conclusions drawn.

Another limitation is the construction of the *Level of REA Training* variable. We realize that our operationalization of this variable only considers the amount of exposure to REA patterns and not the participants' knowledge of REA conceptual modeling structures. The required assumption that the amount of exposure (i.e., low, medium, high) is related to the amount of learning could have been avoided by conducting a pre- or post-test of the participants' REA knowledge (i.e., by measuring the outcome of REA patterns learning).

We are also aware that, independent from the role that pattern recognition plays, the applied diagram transformations might cause the diagrams to be non computationally equivalent. Therefore, ideally, the isolated and combined effects of the applied transformations (i.e., objectification and repositioning diagram elements) should also have been investigated outside a REA patterns recognition context, in order to compare the results. To date, almost no such studies have been conducted. We are aware of only one study that empirically investigated user performance effects of objectification, and this study by Poels, Gailly, Maes, and Paemeleire (2005) concludes that it is plausible that users perform better with the representation (i.e., directly represented or objectified relationships) they are more familiar with (recall that our study participants received training in both ways of representing relationships). The empirical study of diagram layout effectiveness is another excellent opportunity for future research (Moody, 2009).

Finally, we are aware that the use of business student participants as surrogates of real business professionals reduces external validity. Given that there is consensus in the research literature that pattern-based approaches to conceptual modeling are most useful for novice users, we have deliberately defined the target population of our study as novice business professionals in the role of model user. Although strictly spoken, the study participants are not a sample from this population, they do approximate such a sample which alleviates this threat to external validity.

REFERENCES

Ajzen, I. (2002). Perceived Behavioral Control, Self-Efficacy, Locus of Control, and the Theory of Planned Behavior. *Journal of Applied Social Psychology*, *32*(4), 665–683. doi:10.1111/j.1559-1816.2002.tb00236.x

Allen, G. N., & March, S. T. (2006). The Effects of State-Based and Event-Based Data Representation on User Performance in Query Formulation Tasks. *Management Information Systems Quarterly*, *30*(2), 269–290.

Antony, S., & Mellarkod, V. (2004). A Methodology for using Data-modeling Patterns. In D. Batra, J. Parsons, & V. Ramesh (Eds.), *Proceedings of the 3rd Symposium on research in Systems Analysis and Design*. St. John's, NL, Canada.

Bandura, A. (1997). *Self-Efficacy: The Excercise of Control*. New York: W.H. Freeman.

Batra, D. (2005). Conceptual Data Modeling Patterns: Representation and Validation. *Journal of Database Management*, *16*(2), 84–106.

Batra, D., & Sin, T. (2008). The READY Model: Patterns of Dynamic Behavior in REA-Based Accounting Applications. *Information Systems Management*, *25*, 200–210. doi:10.1080/10580530802151103

Batra, D., & Wishart, N. A. (2004). Comparing a rule-based approach with a pattern-based approach at different levels of complexity of conceptual data modelling tasks. *International Journal of Human-Computer Studies*, *61*, 397–419. doi:10.1016/j.ijhcs.2003.12.019

Bodart, F., Patel, A., Sim, M., & Weber, R. (2001). Should Optional Properties Be Used in Conceptual Modelling? A Theory and Three Empirical Tests. *Information Systems Research*, *12*, 384–405. doi:10.1287/isre.12.4.384.9702

Burton-Jones, A., & Meso, P. N. (2008). The Effects of Decomposition Quality and Multiple Forms of Information on Novices' Understanding of a Domain from a Conceptual Model. *Journal of the Association for Information Systems*, *9*(12), 748–802.

Burton-Jones, A., & Weber, R. (1999). Understanding Relationships with Attributes in Entity-Relationship Diagrams. In *Proceedings of the Twentieth International Conference on Information Systems* (pp. 214-228).

Burton-Jones, A., & Weber, R. (2003). Properties do not have properties: Investigating a questionable conceptual modelling practice. In D. Batra, J. Parsons, & V. Ramesh (Eds.), *Proceedings of the 2nd Annual Symposium on Research in Systems Analysis and Design*.

Church, K., & Smith, R. (2008). REA Ontology-Based Simulation Models for Enterprise Strategic Planning. *Journal of Information Systems*, *22*(2), 301–329. doi:10.2308/jis.2008.22.2.301

Connolly, T. M., & Begg, C. E. (2005). *Database Systems: a Practical Approach to Design, Implementation, and Management* (4th ed.). New York: Addison-Wesley.

Dedene, G., & Snoeck, M. (1995). Formal Deadlock Elimination in an Object-Oriented Conceptual Schema. *Data & Knowledge Engineering*, *15*(1), 1–30. doi:10.1016/0169-023X(94)00031-9

Dunn, C., & Grabski, S. (2001). An Investigation of Localization as an Element of Cognitive Fit in Accounting Model Representations. *Decision Sciences*, *32*(1), 55–94. doi:10.1111/j.1540-5915.2001.tb00953.x

Dunn, C. L., Cherrington, J. O., & Hollander, A. S. (2005). *Enterprise Information Systems: A Pattern Based Approach*. New York: McGraw-Hill.

Gailly, F., Laurier, W., & Poels, G. (2008). Positioning and Formalizing the REA enterprise ontology. *Journal of Information Systems*, *22*(2), 219–248. doi:10.2308/jis.2008.22.2.219

Geerts, G., & McCarthy, W. E. (2002). An Ontological Analysis of the Economic Primitives of the Extended-REA Enterprise Information Architecture. *International Journal of Accounting Information Systems*, *3*(1), 1–16. doi:10.1016/S1467-0895(01)00020-3

Geerts, G., & McCarthy, W. E. (2006). Policy-Level Specification in REA Enterprise Information Systems. *Journal of Information Systems*, *20*(2), 37–63. doi:10.2308/jis.2006.20.2.37

Gemino, A., & Wand, Y. (2003). Foundations for Empirical Comparisons of Conceptual Modelling Techniques. In D. Batra, J. Parsons, & V. Ramesh (Eds.), *Proceedings of the 2nd Symposium on Research in Systems Analysis and Design*.

Gemino, A., & Wand, Y. (2005). Complexity and clarity in conceptual modeling: Comparison of mandatory and optional properties. *Data & Knowledge Engineering*, *55*(3), 301–326. doi:10.1016/j.datak.2004.12.009

Genero, M., Poels, G., & Piattini, M. (2008). Defining and Validating Metrics for Assessing the Understandability of Entity-Relationship Diagrams. *Data & Knowledge Engineering*, *64*(3), 534–557. doi:10.1016/j.datak.2007.09.011

Gentner, D., & Medina, J. (1998). Similarity and the development of rules. *Cognition*, *65*, 263–297. doi:10.1016/S0010-0277(98)00002-X

Gerard, G. J. (2005). The REA Pattern, Knowledge Structures and Conceptual Modeling Performance. *Journal of Information Systems*, *19*(1), 57–77. doi:10.2308/jis.2005.19.2.57

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual-Performance. *Management Information Systems Quarterly*, *19*(2), 213–236. doi:10.2307/249689

Gruber, T. R. (1993). A Translation Approach to Portable Ontology Specifications. *Knowledge Acquisition*, *5*, 199–220. doi:10.1006/knac.1993.1008

Haugen, R., & McCarthy, W. E. (2000). *REA, a semantic model for Internet supply chain collaboration.* Retrieved from https://www.msu.edu/user/mccarth4/paplist1.html

Hruby, P., Kiehn, J., & Scheller, C. V. (2006). *Model-Driven Design Using Business Patterns*. New York: Springer.

Irwin, G. (2002). The Role of Similarity in the Reuse of Object-Oriented Analysis Models. *Journal of Management Information Systems*, *19*(2), 219–248.

Jones, R. A., Tsay, J. E., & Griggs, K. (2005). An Empirical Investigation of the Task Specific Relative Strengths of Selected Accounting and Information Systems Diagramming Techniques. *Journal of Computer Information Systems*, *46*, 99–114.

Khatri, V., Vessey, I., Ramesh, V., Clay, P., & Park, S.-J. (2006). Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge. *Information Systems Research*, *17*, 81–99. doi:10.1287/isre.1060.0081

Kim, Y. G., & March, S. T. (1995). Comparing Data Modeling Formalisms. *Communications of the ACM*, *38*(6), 103–115. doi:10.1145/203241.203265

Maes, A., & Poels, G. (2007). Evaluating Quality of Conceptual Modelling Scripts Based on User Perceptions. *Data & Knowledge Engineering*, *63*(3), 701–724. doi:10.1016/j.datak.2007.04.008

McCarthy, W. E. (1982). The REA Accounting Model: A Generalized Framework for Accounting Systems in A Shared Data Environment. *Accounting Review*, *57*, 554–578.

McCarthy, W. E. (2004). The Evolution toward REA Accountability Infrastructures for Enterprise Systems. In *Proceedings of the First International Conference on Enterprise Systems and Accounting,* Thesaloniki, Greece (pp. 1-2).

Moody, D. (2002). Comparative Evaluation of Large Data Representation Methods: The Analyst's Perspective. In *Conceptual Modeling* (LNCS 2503, pp. 214-231).

Moody, D. (2009). The "Physics" of Notations: Towards a Scientific Basis for Constructing Visual Notations in Software Engineering. *IEEE Transactions on Software Engineering*, *35*(6), 756–779. doi:10.1109/TSE.2009.67

Moody, D., & Shanks, G. (2003). Improving the quality of data models: empirical validation of a quality management framework. *Information Systems*, *28*, 619–650. doi:10.1016/S0306-4379(02)00043-1

Nickerson, J. V., Corter, J. E., Tversky, B., Zahner, D., & Rho, Y. J. (2008). *The Spatial Nature of Thought: Understanding Systems Design Through Diagrams.* Paper presented at the 2008 International Conference on Information Systems.

O'Leary, D. E. (2004). On the relationship between REA and SAP. *International Journal of Accounting Information Systems*, *5*, 65–81. doi:10.1016/j.accinf.2004.02.004

Olivé, A. (2007). *Conceptual Modeling of Information Systems*. New York: Springer.

Parsons, J. (2003). Effects of Local versus Global Schema Diagrams on Verification and Communication in Conceptual Data Modelling. *Journal of Management Information Systems*, *19*(3), 155–183.

Parsons, J. (2005). Empirical Research in Conceptual Modeling - Using Experiments to Understand Semantic Expression. *Wirtschaftsinformatik*, *47*(2), 155–156.

Parsons, J., & Cole, L. (2005). What do the pictures mean? Guidelines for experimental evaluation of representation fidelity in diagrammatical conceptual modeling techniques. *Data & Knowledge Engineering*, *55*(3), 327–342. doi:10.1016/j.datak.2004.12.008

Petre, M. (1995). Why Looking Isn't Always Seeing - Readership Skills and Graphical Programming. *Communications of the ACM*, *38*(6), 33–44. doi:10.1145/203241.203251

Poels, G., Gailly, F., Maes, A., & Paemeleire, R. (2005). Object Class or Association class? Testing the User Effect on Cardinality Interpretation. In *Perspectives in Conceptual Modeling* (LNCS 3770, pp. 33-42).

Poels, G., Maes, A., Gailly, F., & Paemeleire, R. (in press). The pragmatic quality of Resources-Events-Agents diagrams: an experimental evaluation. *Information Systems Journal, 21*(1).

Purao, S., Storey, V. C., & Han, T. D. (2003). Improving analysis pattern reuse in conceptual design: Augmenting automated processes with supervised learning. *Information Systems Research*, *14*(3), 269–290. doi:10.1287/isre.14.3.269.16559

Rosli, K., Ahmi, A., & Mohamad, L. (2009). Resource-Event-Agent (REA) Modelling in Revenue Information System (RiS) Development: Smart Application for Direct-Selling Dealers and SMEs. *Journal for the Advancement of Science & Arts*, *1*(1), 43–62.

Ryan, S. D., Bordoloi, B., & Harrison, D. A. (2000). Acquiring Conceptual Data Modeling Skills: The Effect of Cooperative Learning and Self-Efficacy on Learning Outcomes. *The Data Base for Advances in Information Systems*, *31*, 9–24.

Siau, K. (2004). Informational and Computational Equivalence in Comparing Information Methods. *Journal of Database Management*, *15*(1), 73–86.

Siau, K., & Rossi, M. (in press). Evaluation techniques for systems analysis and design modelling methods – a review and comparative analysis. *Information Systems Journal, 21*(1).

Siau, K., Wand, Y., & Benbasat, I. (1997). The relative importance of structural constraints and surface semantics in information modeling. *Information Systems*, *22*(2-3), 155–170. doi:10.1016/S0306-4379(97)00009-4

Smith, D. K., Chang, J., & Moores, T. T. (2003). *Comparing Self-Efficacy and Meta-Cognition as Indicators of Learning.* Paper presented at the 9th Americas Conference on Information Systems.

Topi, H., & Ramesh, V. (2002). Human Factors research on Data Modeling: A review of Prior Research, An extended Framework and Future Research Directions. *Journal of Database Management*, *13*(2), 3–19.

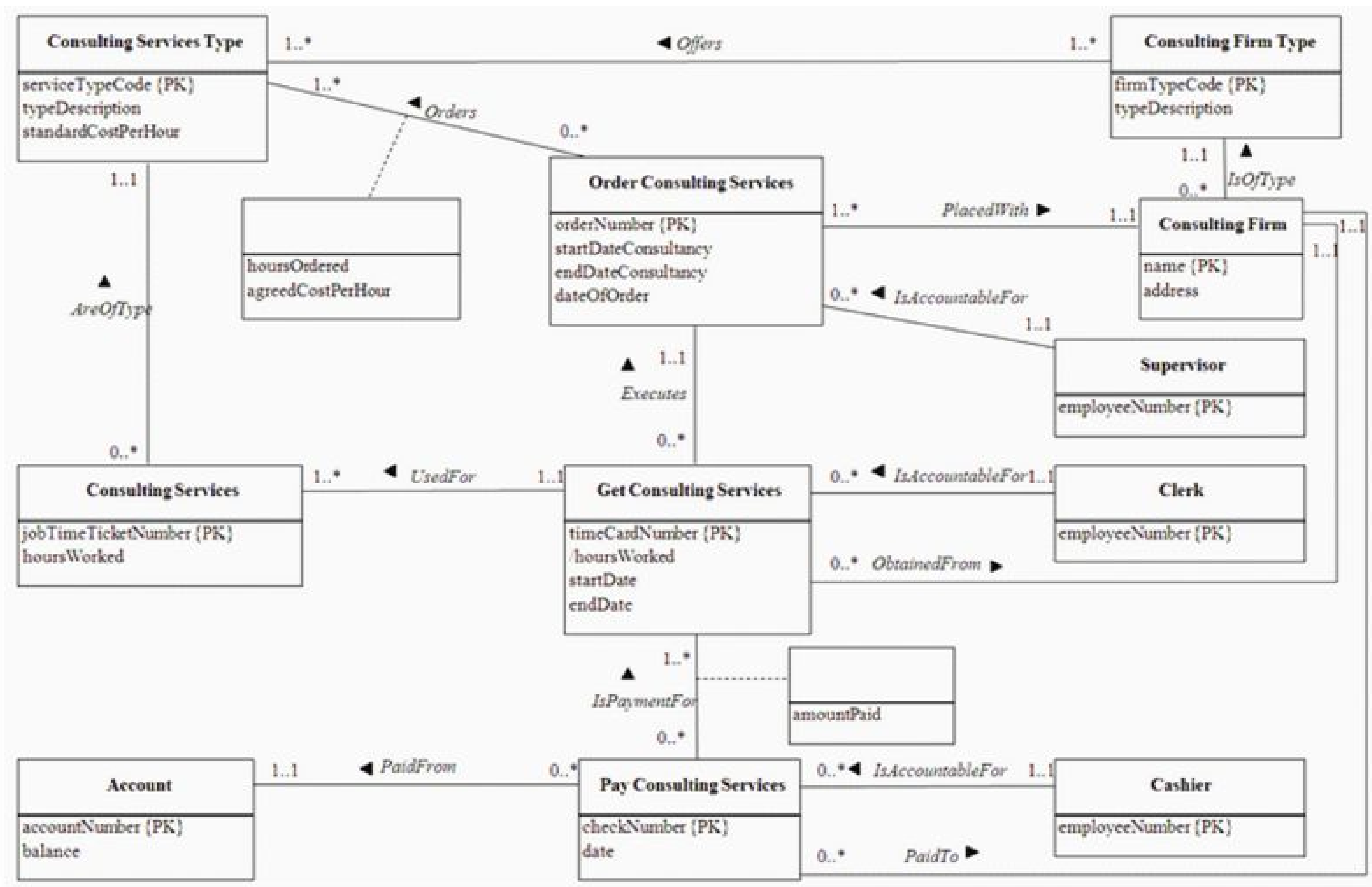
Wand, Y., Storey, V. C., & Weber, R. (1999). An Ontological Analysis of the Relationship Construct in Conceptual Modeling. *ACM Transactions on Database Systems*, *24*, 494–528. doi:10.1145/331983.331989

Wand, Y., & Weber, R. (2002). Research Commentary: Information Systems and Conceptual Modeling - A Research Agenda. *Information Systems Research*, *13*(4), 363–377. doi:10.1287/isre.13.4.363.69

Geert Poels is a professor with the rank of senior lecturer at the Department of Management Information Science and Operations Management, within the Faculty of Economics and Business Administration of Ghent University. He heads the Management Information Systems research group which focuses on conceptual modeling, business ontology, business process management, and Service Science. He is also a part-time professor in software project management at the Center of Industrial Management of the Katholieke Universiteit Leuven. His research was published in IEEE Transactions on Software Engineering, Information Sciences, Information Systems Journal, Data & Knowledge Engineering, *and other academic journals within the information systems and computer science domains.*

APPENDIX

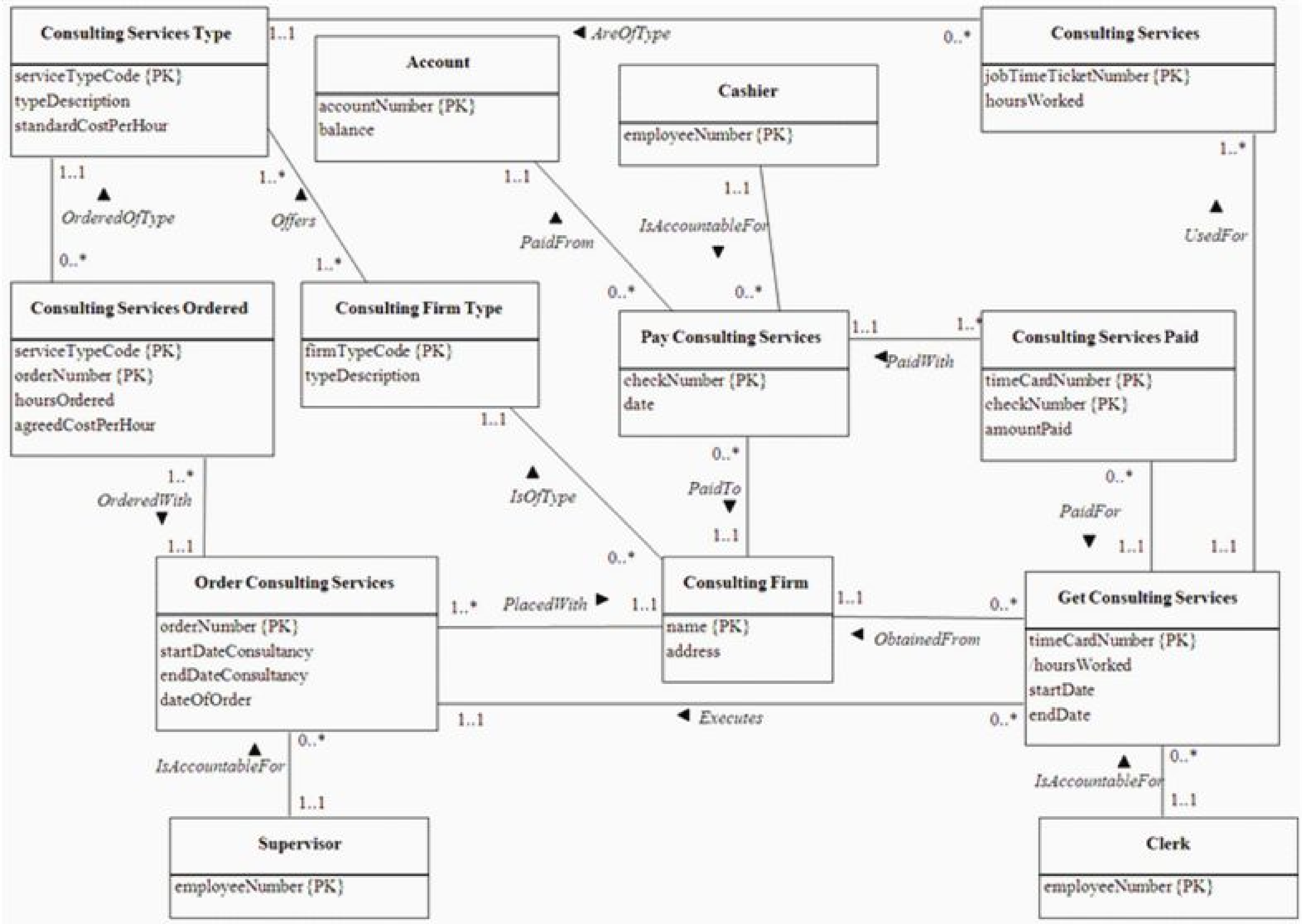
Figure 7. REA diagram



ER Formalism Knowledge Pre-Test Questions

1. Can an entity of type Alpha be related to an entity of type Beta that is not related to an entity of type Gamma?
2. Does the diagram specify an upper limit on the number of entities of type Gamma that are related to the same entity of type Delta?
3. Does every entity of type Gamma have to be related to an entity of type Beta?
4. Can an entity of type Gamma be related to only one entity of type Delta?
5. Should each entity of type Alpha be related to each entity of type Beta and vice versa?
6. Can two or more entities of type Gamma that are related to some entity of type Beta all be related to the same entity of type Beta?
7. Can there be maximum one relationship between some entity of type Gamma and some entity of type Delta?
8. Can an entity of type Gamma be related to more than one entity of type Alpha, via an entity of type Beta?
9. Should an entity of type Beta be related to maximum one entity of type Delta, via an entity of type Gamma?

Figure 8. Non-REA diagram



10. Does every entity of type Alpha have to be related to at least one entity of type Delta, via an entity of type Beta and an entity of type Gamma?
11. Does an entity of type Alpha that is related via a relationship of type Gamma with an entity of type Beta, have to be related via a relationship of type Delta with the same entity of type Beta?
12. Can an entity of type Beta be related to different sets of entities of type Alpha via relationships of types Gamma and Delta?
13. Assume that an entity of type Alpha is related via a relationship of type Delta to some entity of type Beta. Does this entity of type Beta have to be related to the same entity of type Alpha via a relationship of type Gamma?
14. Does there exist a many-to-many entity connection between the types Alpha and Gamma via relationships of the types Chi and Theta with entities of type Beta?
15. Can the entity of type Alpha that has the value "1" for the attribute deltaAlpha and the entity of type Gamma that has the value "x" for the attribute deltaGamma be connected to each other more than once via relationships of the types Chi and Theta with entities of type Beta?

Figure 9. Box 1

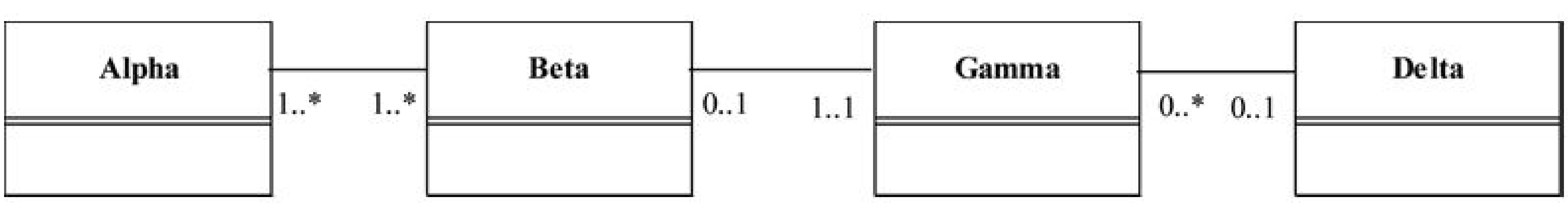
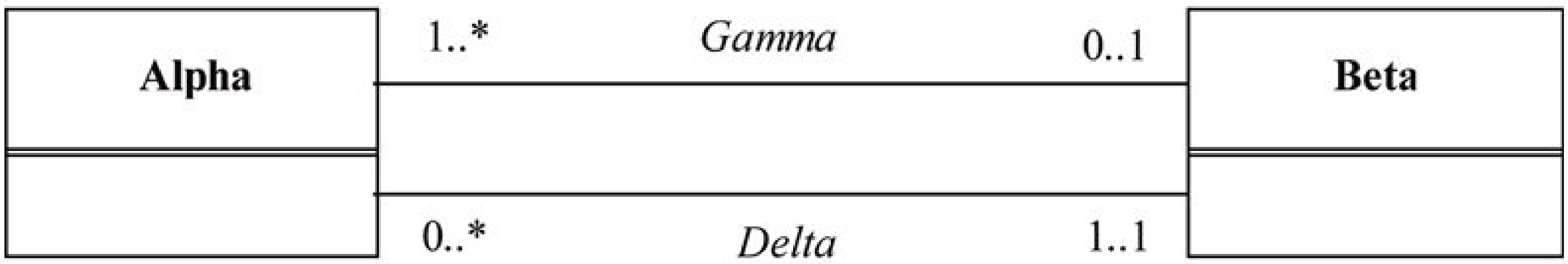


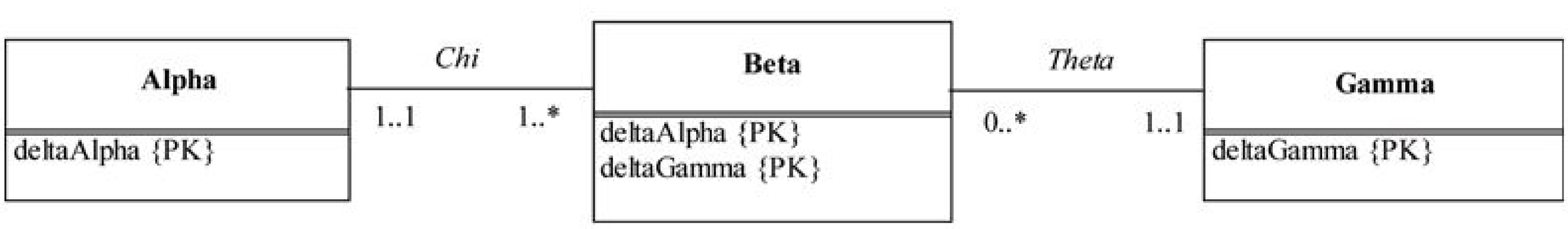
Figure 10. Box 2



Model Comprehension Questions

1. Can consulting services only be obtained from a consulting firm where a supervisor has placed an order?
2. Can a cashier make payments for consulting services which have not been charged to a timecard?
3. Can consulting services with working hours registered on several time cards, be paid for with one single payment transaction?
4. Do all working hours, for jointly obtained and charged consulting services, have to be registered on at least one job-time ticket?
5. Can a supervisor order different types of consulting services with one single order?
6. Can a cashier make a payment to a consulting firm with money drawn from more than one account?
7. Can the consulting working hours that are registered on one and the same job-time ticket, have been obtained on different occasions?
8. Must jointly obtained and charged consulting services belong to a single consulting services type?
9. Must jointly obtained and charged consulting services, be paid with a single payment transaction?
10. Can a cashier make payments for consulting services that have been charged to a timecard, but were not ordered?
11. Must all consulting services obtained from the same consulting firm, be ordered by the same supervisor?
12. Can it be that we do not know which clerk is accountable for a given timecard?
13. Can a type of consulting services be described and be assigned a standard cost per hour without there being any order of this type of services?
14. Must a consulting firm be paid immediately for consulting services charged to a timecard?
15. Can consulting working hours registered on the same job-time ticket be related to more than one order?

Figure 11. Box 3



Measurement Scales

All items are seven-point Likert scales, anchored at "Strongly disagree" and "Strongly agree".

Perceived Self-Efficacy

PSE_before: present tense ("I am able to …")
PSE_after: past tense ("I was able to …")
PSE_1: I am/was able to correctly interpret the meaning of ER Model constructs.
PSE_2: I am/was able to interpret the meaning of ER Model constructs without much effort.
PSE_3: I am/was able to understand the structure of a business process modelled in an ER diagram (i.e. which activities?, who is involved?, …).
PSE_4: I am/was able to quickly see in an ER diagram the structure of a business process (i.e. which activities?, who is involved?, …).
PSE_5: I am/was able to derive the business policies that govern a business process using an ER diagram.
PSE_6: I am/was able to quickly see in an ER diagram the business policies that govern a business process.

Perceived Ease of Interpretation

$PEOI_1$: It was easy for me to understand what the conceptual schema was trying to model.
$PEOI_2$: Using the conceptual schema was seldom frustrating.
$PEOI_3$: Overall, the conceptual schema was easy to use.
$PEOI_4$: Learning how to read the conceptual schema was easy.

User Information Satisfaction

UIS_1: The conceptual schema adequately met the information needs that I was asked to support.
UIS_2: The conceptual schema was efficient in providing the information I needed.
UIS_3: The conceptual schema was effective in providing the information I needed.
UIS_4: Overall, I am satisfied with the conceptual schema for providing the information I needed.