MIS Quarterly

RESEARCH ARTICLE

GUIDELINES FOR DESIGNING VISUAL ONTOLOGIES TO SUPPORT KNOWLEDGE IDENTIFICATION[1]

Palash Bera
A. R. Sanchez, Jr. School of Business, Texas A&M International University,
Laredo, TX 78041 U.S.A. {Palash.Bera@tamiu.edu}

Andrew Burton-Jones and Yair Wand
Sauder School of Business, The University of British Columbia,
Vancouver, BC V6T 1Z2 CANADA {Andrew.Burton-Jones@sauder.ubc.au} {Yair.Wand@sauder.ubc.ca}

Organizations often provide workers with knowledge management systems to help them obtain knowledge they need. A significant constraint on the effectiveness of such systems is that they assume workers know what knowledge they need (they know what they don't know) when, in fact, they often do ***not*** *know what knowledge they need (they* ***don't*** *know what they don't know). A way to overcome this problem is to use visual ontologies to help users learn relevant concepts and relationships in the knowledge domain, enabling them to search the knowledge base in a more educated manner. However, no guidelines exist for designing such ontologies. To fill this gap, we draw on theories of philosophical ontology and cognition to propose guidelines for designing visual ontologies for knowledge identification.*

We conducted three experiments to compare the effectiveness of ***guided*** *ontologies, visual ontologies that followed our guidelines, to* ***unguided*** *ontologies, visual ontologies that violated our guidelines. We found that subjects performed considerably better with the guided ontologies, and that subjects could perceive the benefits of using guided ontologies, at least in some circumstances. On the basis of these results, we conclude that the way visual ontologies are presented makes a difference in knowledge identification and that theories of philosophical ontology and cognition can guide the construction of more effective visual representations. Furthermore, we propose that the principles we used to create the guided visual ontologies can be generalized for other cases where visual models are used to inform users about application domains.*

Keywords: Knowledge work, knowledge identification, visual ontologies, knowledge management system, ontology, cognition

Introduction

Organizations often provide knowledge workers with knowledge management systems (KMSs). Salespeople, for example, rely on KMSs to help them discover how to close sales with customers (Ko and Dennis 2011). Although knowledge resources are designed to make up for users' lack of knowledge, this very lack of knowledge may prevent users from knowing what to look for. The information retrieval literature has recognized a similar problem in information seeking. Belkin et al. (1982, p. 62) state that "in general the user is unable to specify precisely what is needed," a problem which Ford (2004) refers to as an "age-old paradox" (p. 772). Organizations could attempt to overcome this paradox in

[1]Alan Dennis was the accepting senior editor for this paper. Hock Chuan Chan served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

various ways. One approach is to provide an ontology—a description of concepts and their interrelationships in a domain—to help people understand the content available in their knowledge resources. An example by Heflin (2001) demonstrates this idea. When closing sales with customers, salespeople often need to refer to technical product information, for example, to know how the product will behave in a particular situation. Although they generally have access to knowledge bases with technical documentation, salespeople often lack knowledge of the terms used in these documents. As Heflin explains, having an ontology in a knowledge portal can help salespeople learn what concepts are important in the domain and how they are related. This can help them identify useful keywords for searching the knowledge base and help them understand the meaning of the documents they retrieve.

Ontologies are usually provided to users as graphical depictions of concepts and relationships because visual information is extremely helpful for people who need to learn about a domain (Mayer 2001; Turetken and Sharda 2007). Although many researchers have explained the benefits of having visual ontologies in KMSs, little guidance has been offered for how to design them, and to our knowledge, no guidance has been offered for the specific purpose of facilitating knowledge identification. The premise of our study is that the design of visual ontologies can be improved by using principles from *philosophical* ontology. Philosophers in this field create ontologies that describe the "order and structure of reality in the broadest possible sense" (Angeles 1981), for example, describing the world in terms of things, properties, and events. Computer scientists, in contrast, create computer-readable ontologies that describe specific application domains, such as customers, products, and orders in the sales domain (Gomez-Perez et al. 2004). Typically, the individuals who design computerized ontologies do not draw on principles developed in philosophical ontology (Gomez-Perez et al. 2004), but we believe that it would be useful to do so because philosophers have "worked for hundreds of years in an effort to resolve important ontological problems" (Weber 2003, p. 16). We test our proposal by

1. Using principles from philosophical ontology to suggest design guidelines for visual ontologies. We refer to ontologies that follow these guidelines as *guided* ontologies.

2. Evaluating if individuals with guided ontologies perform knowledge identification tasks more effectively than individuals with *unguided* but typical visual ontologies.

To scope our work, we examine one visual ontology language and one philosophical ontology: Web Ontology Language (OWL), the most widely used visual ontology language (Fliedl et al. 2010), and Bunge's (1977) ontology, the most widely used philosophical ontology in IS research (Fonseca 2007). By following this approach, we aim to contribute to research by (1) proposing guidelines derived from a philosophical ontology that can be used to improve visual ontologies and (2) instantiating the proposal for a specific ontological language. In addition, we develop an empirical method to test the usefulness of the guidelines.

In the next section, we outline the practical problem our paper addresses and present our guidelines and their theoretical rationale. We then describe the hypotheses we used to test our ideas, three experiments we conducted to test these hypotheses, and their results. We conclude by discussing the contributions and limitations of the study, and suggesting future research directions.

Designing Visual Ontologies for Knowledge Identification

Knowledge identification refers to the task of identifying what knowledge an individual needs to perform his or her work. *Knowledge* can be interpreted in many ways (Spender 2003), but our study uses a definition from Newell (1982), who studied the nature of knowledge in systems. This definition fits the practical focus of our study, which is to search for knowledge in systems. Newell argued that knowledge can be distinguished from the symbols used to represent it. Knowledge, he argued, is tied to agents, actions, and goals. Specifically, *agents* use knowledge to determine what *actions* to take to attain their *goals*. In this context, a goal refers to a future state of affairs that typically differs from the current state (Luck and Inverno 2001). For example, an *agent* could be a salesperson, the *goal* could be to sell, and the *actions* would be the steps that the salesperson must perform to move from the current state (no sale) to the goal state (having made a sale). This view of knowledge is consistent with pragmatist philosophy, in which knowledge is tied to tasks and the actions taken to accomplish them (Blosch 2001).

Newell's definition of knowledge is well known and accepted in artificial intelligence (AI) (Musen 2004), but this is just one application area; Newell's (1982) definition was intended to be general. It also matches the way in which many IS researchers view KMSs. For example, Gallupe (2001) argued that KMSs should be designed to store knowledge that will help workers find out what they need to know to solve a problem (move to a desired state). Accordingly, we draw on Newell's view of knowledge to define knowledge identification:

> **Knowledge identification**: *the task of asking the right questions to determine what actions need to be taken to change the current state of affairs to a goal state*.

To clarify the meaning of knowledge identification, consider how it differs from problem solving. Problem-solving refers to a complex, goal-directed task performed by an agent (Ashcraft 2002). Performing a task entails taking actions, which in turn requires the agent to know what actions to take. Knowledge is the ability to identify what actions to take to solve the problem. An agent who lacks this knowledge will need to identify the necessary knowledge. This means finding out what to ask to identify the actions to take. The agent will then need to seek the identified knowledge. For example, assume that a salesperson needs to sell a product to a client. The *problem-solving* task is working out how to make the sale, such as first determining the client's priorities. *Knowledge* is the ability to identify what actions to take to do this, such as finding out the client's priorities by asking staff who have previously sold to the client. Salespeople who do not have this knowledge will need to engage in *knowledge identification*, namely, identifying the questions they need to ask to determine what actions to take. For example, a novice salesperson might identify the following question: Is there a particular person I should speak with to find out the client's priorities?

Although problem-solving often requires knowledge identification, the relationship between the two can be complex. For example, once a salesperson has discovered that he or she should talk to other staff who have previously sold to the client, a new problem arises (contacting the relevant staff), which requires knowledge (the ability to identify what actions to take to make contact), which in turn might require further knowledge identification (asking questions to determine what actions to take, such as asking how to contact a particular person). Although we recognize the complex relationship between knowledge identification and problem-solving, our focus is on *knowledge identification*. Because problem-solving often requires knowledge identification, our guidelines should facilitate problem-solving as well, but we leave this for future research.

Using Visual Ontologies to Support Knowledge Identification

Several tools have been created to represent ontologies visually in KMSs, such as the Protégé-OWL plugin (Protégé 2003), QuizRDF (Davies et al. 2002), and KAON (Motik 2002). Each tool uses a specific ontology language. Our study uses OWL, implemented in Protégé, arguably the most widely used ontology development tool (Horridge et al. 2004). OWL describes ontologies in terms of classes, individuals, properties of classes, properties of individuals, and assertions about properties. For a brief description of OWL, see Appendix A.

OWL was developed as part of the infrastructure for the Semantic Web (Gomez-Perez et al. 2004). As a result, it can be used to describe information on the Web and in any Web-accessible system, such as a KMS attached to a corporate intranet or extranet (Daconta et al. 2003). Because of its formality, OWL can be used to specify domains clearly and precisely. In addition to OWL being highly applicable to modern KMSs (Fensel 2003, Linden 2005), tools for constructing visual OWL ontologies are widely available (Protégé 2003) and used (Zou 2004). For these reasons, we chose to use OWL in our study.

To demonstrate how a visual ontology in OWL can facilitate knowledge identification, consider a visual ontology that a travel agency might provide to help its employees understand how the agency works. Figure 1 shows an excerpt. In Table 1, we provide an example of how such an ontology could be used for knowledge identification. Recall that knowledge identification involves identifying the questions that need to be asked to determine what actions to take to change the current state of affairs to a goal state. In Table 1, the current state is that customers do not know their reservations have to be changed. The goal state is that customers are fully informed about the change. As the example in Table 1 shows, the ontology could help agents come up with several relevant questions, the answers to which would help them in informing customers.

Although our example shows that an ontology can facilitate knowledge identification, one concern readers may have is that the ontology in Figure 1 cannot facilitate it very well because knowledge identification involves asking questions related to state changes, and Figure 1 does not show precisely *how* changes of state occur. This limitation stems from using OWL because OWL offers no syntax for showing actions or changes of state.

There could be several ways to address OWL's inability to show state changes. One is to choose a different ontology language, but we are not aware of any visual ontology languages that allow modelers to show how state changes occur. Another approach is to design an entirely new language or to modify OWL's syntax so that it shows state changes explicitly. We have chosen a different path, taking the view that we can keep the existing OWL syntax and improve the extent

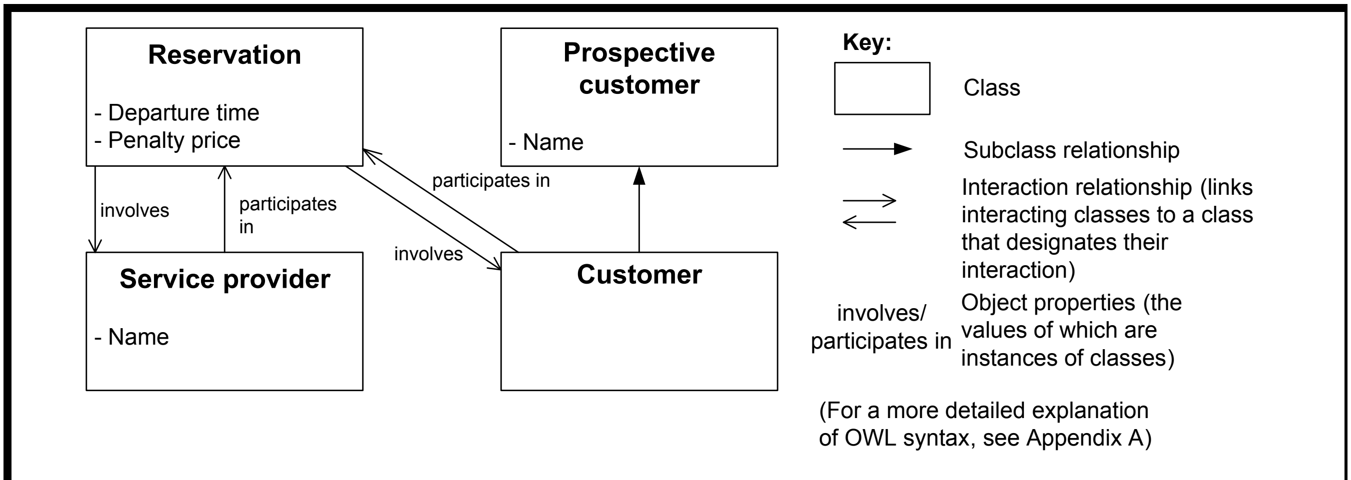


Figure 1. An Excerpt of a Visual Ontology for a Travel Domain

Table 1. Using an Ontology for Knowledge Identification: An Example

Sample problem: A travel agent needs to inform customers about a change in departure time caused by a problem with a particular service provider.

Relevant knowledge identification (KI) task: What questions does the travel agent need to ask to find out what to do?

Relevant responses to the KI task	Why the responses are relevant	Why the diagram helps identify these responses
1. How can we determine which reservations are impacted?	The travel agent needs to inform only those customers participating in reservations in which the service provider is involved.	The diagram shows that the only way in which service providers and customers are related is through the reservations in which they are involved.
2. How might these reservations be impacted?	Additional actions may be required depending on the impact (e.g., the travel agent may need to contact customers in sequence based on who is impacted most).	The diagram shows that customers have reservations with associated departure times and penalty prices. This suggests several possible impacts; for example, departures may be missed, new reservations may need to be made, and penalties may need to be enforced or waived.

to which it supports knowledge identification. Although OWL has no syntax to *directly* show how state changes occur, it is possible to *indirectly* show how they occur. We believe that, when an OWL ontology is used for knowledge identification, showing this information indirectly will be much better than not showing it at all, and that even with this drawback, OWL is the best choice of visual ontology language because of its widespread availability and applicability to KMSs.

Figure 1 was created with the guidelines proposed in this paper. In the next sections, we present these guidelines, explain how they were derived, and explain why guided OWL ontologies should support knowledge identification more effectively than unguided ontologies.

Philosophical Guidance to Develop Visual Ontologies in OWL

Because philosophical ontologies describe the static and dynamic aspects of the world in general (Angeles 1981), they are useful theories to turn to when trying to represent a general feature of the world, such as how state changes occur. Several philosophical ontologies exist. We use Bunge's (1977) ontological theory because: (1) compared with other ontologies (Chisholm 1996; Guarino and Welty 2002; Sowa 2000), it offers a clear formalization for representing states of things and how state changes occur, and (2) researchers have shown that it can be used to improve visual representations (Burton-Jones and Meso 2006; Gemino and Wand 2005). This is only the second study to explore how Bunge's ontology can be used to improve OWL ontologies (Bera et al. 2010) and it is the first study to use Bunge's ontology in the context of knowledge identification.

Bunge's (1977) ontology specifies certain relationships among things, properties, and classes. In particular, all things have properties and properties are always attached to things. In Bunge's ontology, a property that is inherently a property of a thing is an *intrinsic property*, and a property that is meaningful only in the context of two or more things is a *mutual property*. Age is an example of an intrinsic property, and the salary of an employee, which is mutual to an employee and a firm, is an example of a mutual property. Properties are modeled as state functions, the values of which form the *state* of the thing. For example, the attribute "smoothness" reflects physical properties of the surface of a thing and could have values varying from smooth to rough.

In Bunge's ontology, interactions among things cause changes of state. A thing *acts on* another if it affects the states the other thing traverses. Two things *interact* if at least one acts on the other. An interaction is manifested by mutual properties of the interacting things; the change of such properties is observed as a change of state. For example, when a company hires someone, the act of hiring changes that person's state from "non-employee" to "employee" and the company and person will now share one or more new mutual properties, such as a salary.

We draw on Bunge's ontology to conclude that the notion of a mutual property can be used to show indirectly how state changes occur because (1) state changes occur as a result of interactions, and (2) mutual properties manifest the existence of interactions. Thus, modelers who create OWL ontologies could indirectly show how state changes occur in a domain by distinguishing between mutual properties and the intrinsic properties of things in the domain.

Unfortunately, OWL syntax does not explicitly distinguish between mutual properties and intrinsic properties. To determine if we could make that distinction in OWL diagrams, we mapped the constructs in OWL onto the concepts in Bunge's ontology. It became clear that the constructs in OWL could be interpreted in a similar way to the constructs in some conceptual modeling languages, such as class diagrams in the Unified Modeling Language (UML). Thus, we turned to work by Evermann and Wand (2005) that offered a way to distinguish intrinsic properties from mutual properties in class diagrams. Evermann and Wand proposed that intrinsic and mutual properties could be distinguished by using two types of classes: *regular classes*, which have intrinsic properties, and *interaction classes*, which show bundles of mutual properties that manifest interactions among things in the domain. Extending this proposal, ontology designers should be able to show indirectly how state changes occur in a domain by distinguishing between *entity classes*, which represent types of entities in the domain, and *interaction classes*, which represent bundles of properties arising from interactions among entities (where entities are instances of entity classes). If instances of an entity class can engage in an interaction, we refer to that class as an *interacting class*. The benefit of distinguishing entity classes from interaction classes is that it helps to explicate the ways in which entities interact in a domain. Specifically, if users are given a domain ontology that makes this distinction, they will be more able to identify the interactions in which entities can be or are involved.

To make these ideas actionable, we created the guidelines in Table 2. Appendix B lists rules to help modelers implement these guidelines. There are very few guidelines for developing formal ontologies (Gomez-Perez et al. 2004), particularly for creating OWL ontologies in ways that people find clear and understandable (Fliedl et al. 2010). Our guidelines help to fill this gap.

In the field of conceptual data modeling, the general idea of using different types of classes to show interactions has existed for some time (e.g., Ram 1995). Some techniques even offer special notation that can be used in such situations. For example, Evermann and Wand showed how researchers can use the *association class* notation in UML (Rumbaugh et al. 1999) for this purpose; the *relationship-with-attributes* notation in the ER grammar can be used similarly. However, the meaning of such notation has never been very clear because these notations were primarily devised to model databases or software rather than real-world domains (Wand et al. 1999) and the most appropriate way of using them in conceptual modeling remains an open research question (Burton-Jones and Weber 1999; Parsons and Cole 2005). Even if these conceptual modeling notations were ideal, it would not help in our case because we are utilizing OWL and OWL offers no specialized notation (such as association classes or relationships-with-attributes) to show interactions. Overall, our contribution lies not in the general idea of distinguishing between interacting classes and interaction classes, but rather in applying this idea to model organizational domains in OWL for the purpose of supporting knowledge identification.

The Benefits of Guided Ontologies: Theory and Illustration

Up to this point, our argument has been that because knowledge is tied to state changes, domain ontologies must show

Table 2. Guidelines from Ontological Theory to Show State Changes in OWL
1. Identify classes that have instances that interact with instances of other classes. Model these classes as *interacting classes*. Model the interactions as *interaction classes*.
2. Identify the properties of the interaction classes. In the sense of Bunge's ontology, these properties are mutual properties of entities in the interacting classes that are engaged in the specific interaction.
3.* For each interaction class, indicate the interacting classes that have instances linked by these interactions. A prefix (e.g., "involves") can be used to indicate OWL properties that represent the link from interaction to interacting classes.
4.* For each interacting class, indicate the interaction classes in which it can participate. A prefix (e.g., "participates in") can be used to indicate OWL properties that represent the link from interacting to interaction classes.

*In 3 and 4, the OWL properties are object properties (properties whose values are instances of other classes).

how such changes can come about if they are to facilitate knowledge identification. Although OWL ontologies cannot show state changes explicitly because they lack the proper syntax, guided ontologies can still facilitate knowledge identification. Three theories support this claim. First, Bunge's ontological theory supports the claim because it suggests that guided ontologies can provide individuals with clues about how state changes occur because they highlight interactions, and interactions cause state changes to occur.

Two theories of cognition also support our claim: cognitive fit theory and multimedia learning theory. *Cognitive fit theory* suggests that when individuals need to solve problems in a domain (where "problems" are defined broadly to include complex tasks such as knowledge identification), their performance will improve if the representation of the problem matches the representation of the domain (Shaft and Vessey 2006). Both types of representations can exist externally to individuals, such as a textual problem description and a visual ontology of a domain, and internally, in individuals' minds (Zhang 1991). According to this theory, individuals should perform knowledge identification tasks more effectively when they have guided ontologies because these tasks require individuals to understand how state changes occur and guided ontologies provide explicit clues about how those changes occur; unguided ontologies do not. In other words, the aspects related to state changes are made *salient* in guided ontologies.

Cognitive fit theory does not specify the *extent* to which two representations should differ for one to provide a better fit. This leaves a gap in our theory because guided ontologies do not show state changes explicitly; they just provide clues about such changes. *Multimedia learning theory* fills this gap because it suggests that even small differences in representations can be helpful if the differences are relevant to the task (Mayer 2001). When individuals use representations as they perform tasks, they are often faced with many stimuli to process (e.g., different task and representation elements). In such cases, even simple cues, such as highlighted images or words, can help individuals select, process, and integrate relevant pieces of information internally, which in turn helps them perform the tasks (Mayer and Moreno 2003). This suggests that, even though guided ontologies provide only clues about state changes, such clues could be very helpful when individuals are performing tasks that need such information.

Consider the travel example. Figure 2 shows the guided ontology and three types of unguided ontologies. (Figures C5 through C8 in Appendix C provide the complete versions created with Protégé.) For any domain, numerous unguided ontologies could exist, some worse and some better than those in Figure 2. The three types shown here simply represent different ways of violating the guidelines that might occur in practice. Overall, the guided ontology in Figure 2 differs from the unguided ontologies in three ways by showing explicitly

- all relevant interacting and interaction classes
- how these classes relate (through the "involves" and "participates in" links)
- the mutual properties associated with the interaction (as attributes of the interaction class)

In Table 3, we provide reasons why the guided ontology in Figure 2A should help individuals perform knowledge identification tasks more effectively than any of the unguided versions. As the examples in Table 3 show, it is still *possible* for individuals to come up with relevant questions (responses) to a knowledge identification task when they are given an unguided ontology. Even so, our claim is that individuals will perform more effectively when they are given a guided ontology because guided ontologies provide more explicit clues about how state changes might occur. In Figure 2, the clue is that departure times are set during reservations (a type of interaction). Thus, a change in a reservation will affect both service providers and customers and could also affect *other* elements of the interaction, resulting, for example, in the need for new reservations or penalties to be waived or enforced.

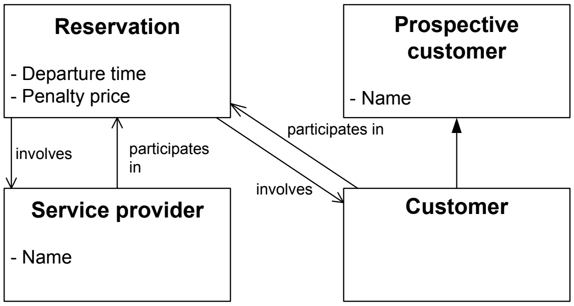


Figure 2A. Guided Ontology
Excerpt from Figure C5, Appendix C
[Complies with guidelines 1–4]

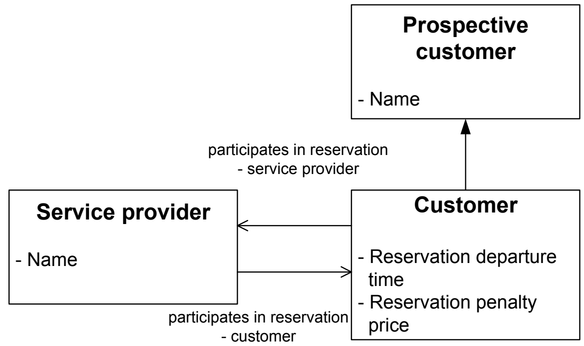


Figure 2B. Unguided Ontology (Type 1)
Excerpt from Figure C6, Appendix C
[Violates guidelines 1–4 by failing to represent the interaction class]

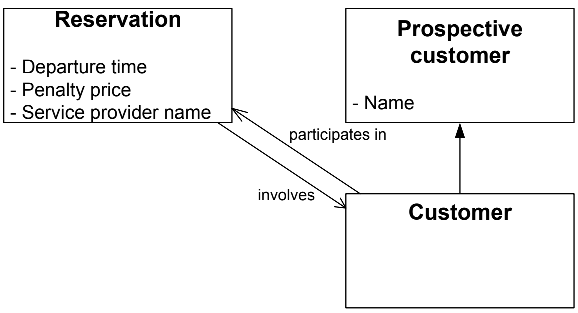


Figure 2C. Unguided Ontology (Type 2)
Excerpt from Figure C7, Appendix C
[Violates guidelines 1, 3, and 4 by failing to represent an interacting class

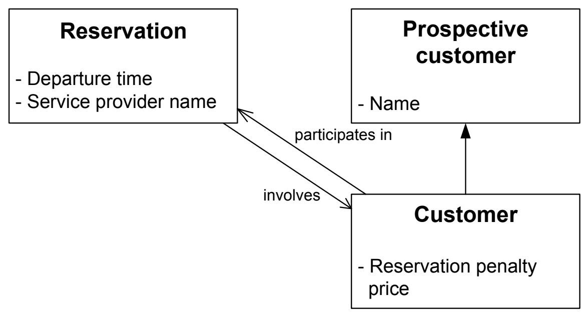


Figure 2D. Unguided Ontology (Type 3)
Excerpt from Figure C8, Appendix C
[Violates guidelines 1–4 by failing to represent an interacting class and misplacing a mutual property]

Figure 2. Guided and Unguided Ontologies of the Travel Domain

Hypotheses

On the basis of the preceding arguments, we propose that individuals given a guided ontology will perform knowledge identification tasks more effectively than they would with an unguided ontology. To test this proposition, we offer three hypotheses: one regarding the *outcome* of using guided ontologies in knowledge identification and two focused on the *process* of doing so.

Our main hypothesis focuses on the outcome of using guided ontologies. We have argued that knowledge is tied to state changes, and guided ontologies—by representing interactions more explicitly—provide more clues about how state changes occur than do unguided ontologies. The theory of cognitive fit and multimedia learning theory both suggest that these clues, even if subtle, can help users of these ontologies in knowledge identification tasks. Thus, we propose

> ***Hypothesis 1**: Subjects conducting knowledge identification using guided ontologies will perform better than subjects using unguided ontologies.*

Our secondary hypotheses focus on the *process* of using guided ontologies. Both cognitive fit theory and multimedia learning theory suggest that external representations of a domain (such as visual ontologies) that fit a task are beneficial because they are organized in a way that highlights the information that individuals need to select and process in order to perform the task (Mayer and Moreno 2003; Shaft and Vessey

Table 3. Illustrating the Benefits of a Guided Ontology for Knowledge Identification	
Sample problem: A travel agent needs to inform customers about a change in departure time caused by a problem with a particular service provider. **Relevant knowledge identification (KI) task**: What questions does the travel agent need to ask to find out what to do?	
Relevant questions (responses) to the KI task	**Why the guided ontology should be more effective than the unguided ontologies in helping individuals identify such questions**
1. How can we determine which reservations are impacted?	Figure 2A shows that service providers are related to customers only through reservations. Therefore, to inform the right customers, the travel agent needs to focus on those who have reservations in which the service provider is involved. In Figures 2B–2D, the fact that service providers are related to customers through reservations is not as salient because these figures show either the service provider class *or* the reservation class but not both.
2. How might these reservations be impacted?	Figure 2A suggests that reservations could be impacted in various ways; for example, the customer could miss a departure and need a new reservation, and penalties may need to be enforced or waived. In Figure 2B, the impact on reservations is not clear because there is no reservation class. The impact is a little clearer in Figures 2C and 2D, because they show the reservation class, but with these figures, users may be less likely to even identify this question because they do not show that the service provider participates in the reservation (i.e., the relevant information is not salient).

2006). Representations without this fit are problematic because to perform the task effectively, individuals must mentally reorganize the representation to clarify what information they need to select and process. Reorganizing a representation in that manner takes effort and may not be performed effectively. Thus, when individuals use a representation that has a higher level of fit with their task, they should (1) find that they *understand* the representation more effectively, because they are more likely to be able to select and process the information required by their task, and (2) find their representation to be *easier* to understand, because there is less need to mentally reorganize the information to perform the task. Thus,

> ***Hypothesis 2***: *Compared to subjects conducting knowledge identification tasks with unguided ontologies, subjects conducting knowledge identification tasks with guided ontologies will perceive*
>
> > ***H2a***: *that they have a greater understanding of the information in the ontology.*
> >
> > ***H2b***: *that the information in the ontology is easier to understand.*

To summarize, our independent variable (and treatment) is the use of guided versus unguided ontologies in knowledge identification tasks. The dependent variables are performance in knowledge identification, perceived understanding, and perceived ease-of-understanding.

Experimental Approach

We conducted three laboratory experiments to test our hypotheses. We chose an experimental setting rather than a field setting because this is the first test of our theory, therefore internal validity was more critical to us than external validity (Calder et al. 1981).

The first two experiments addressed the challenge of choosing a control condition. This was a challenge because we wanted to test our guidelines against the status quo condition of no guidelines, but in principle there could be numerous unguided ontologies, so the appropriate control condition to use was not clear. As Table 4 shows, we addressed this challenge by designing two experiments. In Experiment 1, we chose an ontology from practice that was not created with our guidelines (hence unguided) and we modified it with our guidelines to create the guided version. In Experiment 2, we worked backward, first creating a guided ontology and then creating three unguided versions that violated the guidelines in different ways. The first approach maximizes realism; the second maximizes empirical control. Although either could be done first, we decided to run Experiment 1 first to test the overall effect of the guidelines and demonstrate that the issue can be salient in practice. We then ran Experiment 2 to probe more deeply the precise differences between guided and unguided ontologies that matter.

Table 4. Strategies for Testing Design Guidelines When No Alternative Guidelines Exist

Experiment 1: Use an ontology created in practice (an *unguided* ontology) and revise it so that it follows the guidelines (becoming a *guided* ontology)	**Experiment 2**: Create an ontology that follows the guidelines (a *guided* ontology) and revise it so that it violates them (becoming an *unguided* ontology)
Strengths: • The unguided ontology is a realistic example of at least some ontologies in practice Weaknesses: • The unguided ontology might not represent all potential unguided ontologies • The unguided ontology may violate a complex combination of our modeling guidelines • The guided ontology may have some aspects that are not due to the modeling guidelines but instead carry-over from the unguided ontology Overall: • Greater realism but less empirical control	Strengths: • The guided ontology will be a pure reflection of the guidelines (no carryover effects) • The researcher can create pure unguided ontologies (ontologies that differ from the guided ontology only via their violations) • The researcher can create different unguided ontologies that violate different guidelines Weaknesses: • The researcher cannot be certain that the unguided ontologies reflect those in practice Overall: • Greater empirical control but less realism

A third experiment was then conducted to confirm whether our results truly supported our theory. This was necessary because our theory relied on assumptions about individuals' cognitive processes, but Experiments 1 and 2 did not obtain evidence of these *processes* per se. Experiment 3 used protocol analysis to open the "black box" of individuals' cognitive processes and determine the extent to which they were in line with our theory. We describe each experiment in turn below.

Experiment 1

The aim of Experiment 1 was to determine if our hypotheses would be supported when we used an OWL ontology from practice as the control condition.

Method

Subjects. Because the area of practice examined in this study is still emerging, it was not feasible to identify a representative set of practitioners who use visual ontologies in OWL for knowledge identification. We recruited undergraduate business students as substitutes, randomly assigning them to the treatments. We chose students who had taken two courses (Introduction to MIS and Accounting Information Systems) that both included a brief introduction to data modeling concepts, such as classes and properties. In this way, the subjects would understand the diagrams in the experiment with only one hour of preexperiment training. The subjects were offered $20 for participation and a one-in-four chance at receiving $20 based on their performance.

To determine sample size, we ran a pilot test with 22 subjects. The average correlation between the treatment and knowledge identification scores for the two domains (with 22 subjects) was 0.44, suggesting a large treatment effect (Cohen 1988). Assuming that the effect would be similar, we recruited 56 students to participate, which is a large enough sample to detect a significant difference between means if the effect is indeed large (Cohen's d = 0.9).

Task. Because we could not find any tasks in prior research that test individuals' abilities to identify knowledge using visual ontologies, we created a new task. Perhaps the most direct way to test knowledge identification would be to give subjects a domain ontology and ask them to identify knowledge using it, but this would not work because the term *knowledge* is so ambiguous (Spender 2003). To overcome this problem, we adapted the notion of the *transfer task* from research in conceptual modeling and educational psychology.

In the transfer task, researchers give subjects a diagram of a domain together with a description of problems in the domain and ask subjects to come up with solutions to the problems by making inferences from the diagram (Gemino and Wand 2005; Mayer 2001). We had to adapt this task for our study because the transfer task tests problem solving, and we wanted to test knowledge identification. Therefore, rather than present subjects with a problem and ask them to use the diagram to solve the problem, we presented subjects with a description of a current state and asked them to use the diagrams to come up with questions they would need to answer if they (or someone else) were to change the current state to a specified goal state.

To make this task more concrete, we used the notion of a *procedure* to define the steps that someone would need to take to change the current state to a goal state. To illustrate, one of the knowledge identification tasks in the experiment was

> You are asked to develop a procedure for allowing customers to change their reservations. Using the diagram as guidance, please specify the questions you will ask in order to develop a procedure for allowing customers to change their reservations.

Note that *procedure* in this task refers to a set of steps that customers could follow to change a reservation's current state to a goal state. A good response would be "How should service providers be informed of the change?" because if customers can change their reservations, the procedure should ensure that service providers are notified.

Treatment. Our treatment is the use of guided versus unguided ontologies. We used diagrams of two domains to ensure that our results were not context-specific. We chose auction and travel as the two domains because we expected them to be moderately familiar to subjects (neither extremely familiar nor extremely unfamiliar), which our pretests subsequently confirmed (average auction domain knowledge = 4.21/7.00; average travel domain knowledge = 3.97/7.00). It was important to choose moderately familiar domains because, although prior domain knowledge was not a construct of interest in our study, it can strongly affect how people interpret diagrams (Pretz et al. 2003).

For each domain, we selected excerpts from ontologies that were developed and are used in practice. These ontologies are available in formal OWL notation at www.schemaweb.info, a nonprofit portal for sharing ontologies (Zou 2004). The excerpts served as our unguided ontologies. We then applied our guidelines (Table 2) to them to create the guided versions. Figures C1 through C4 in Appendix C show both versions.

An implication of choosing diagrams from practice is that we did not control *which* guidelines were violated or *how* they were violated. In Appendix C, we annotated the unguided diagrams (Figures C2 and C4) to show the violations in each one. Briefly, however, they violated all our guidelines, but they did so in different ways in different parts of the diagrams. For example,

- Violations of Guideline 1: The guided auction ontology shows an interacting class Seller[2] that is just a property in the Auction class in the unguided ontology. Likewise, the guided auction ontology shows the interaction class AuctionedAt to show how AuctionItems and AuctionHouses interact. The unguided ontology shows this only implicitly by giving the Auction class the hasAuctionItem property.

- Violations of Guideline 2: In the guided travel ontology, the interaction classes InitialItinerary and FinalItinerary each contain a set of properties. In the unguided version, some of these properties are not shown, or not shown clearly. First, the involvesServiceProvider property in the guided ontology is not shown in the unguided version. Second, the involvesTravelAgent property in the guided version is not shown clearly in the unguided version. The unguided ontology shows the property travelAgent, but it is not clear that this property reflects an interaction with another (interacting) class.

- Violation of Guidelines 3 and 4: The guided ontologies include OWL object properties in the interaction and interacting classes (prefixed with Involves and ParticipatesIn, respectively). These object properties are not shown in the unguided ontologies. By violating Guideline 1, the unguided ontologies automatically violate Guidelines 3 and 4 by failing to show how interacting classes participate in interactions (such as, in the auction ontology, failing to show how an AuctionHouse participates in a Bidding interaction).

Another implication of choosing diagrams from practice is that some of the decisions made in creating the unguided versions are carried over into creation of the guided versions. For example, the guided travel ontology (Figure C1) shows a relationship between the Reservation and FinalItinerary classes. Our guidelines do not suggest having such a link but neither do they proscribe it. Therefore, we left it in the guided version because it was in the unguided diagram.

One final issue that we considered when creating the diagrams was informational equivalence. We did so because recent studies had recommended that when researchers test individuals' ability to understand alternative diagrams of a domain, they should ensure that the diagrams are informationally equivalent (Gemino and Wand 2004; Parsons and Cole 2005). This raised a problem for us because applying our guidelines led to differences in the information content of the diagrams. To address this problem, we sought a way to faithfully test our guidelines while adhering as much as possible to the recommendations to preserve informational equivalence. To do this, we went through both sets of diagrams and added terms back to the unguided versions to make the terminology in each diagram as equivalent as possible.

[2]For clarity, we use a different font when referring to specific elements in the diagrams.

Consequently, all terms shown in the guided ontologies are also shown in the unguided ontologies except for Involves and ParticipatesIn. For example, we split the Itinerary class into InitialItinerary and FinalItinerary classes in the unguided travel ontology and we added WinningBidding and ItemsSold classes to the unguided auction ontology. After we performed this procedure, the unguided and guided ontologies incorporated the same set of terms. This change made our test more conservative because it reduced the difference between the diagrams. In other words, if we still obtain an effect, it should be less than what it could have been in practice.

Dependent Measures. We have three dependent measures: knowledge identification performance, perceived ease-of-understanding, and perceived understanding (see Appendix D for the measurement instruments).

To measure knowledge identification performance, we developed three knowledge identification questions for each domain. The wording of the questions was similar to that in past studies using the transfer task (Gemino and Wand 2005). One question used in the experiments (for the travel domain) was shown earlier; the full set is included in Appendix D. Because we have two domains (auction and travel), we have different questions for each domain. An implication of this is that we cannot compare the results for the knowledge identification tasks across the two domains. This does not matter, however, because our aim is not to compare the domains; our interest is solely in the effect of our guidelines in each domain.

Each knowledge identification question allowed subjects to submit as many answers as possible. The first researcher, together with an independent domain expert for each domain, came up with a list of "correct" answers to each question. Because such a list is subjective, we hired two independent coders (Ph.D. students) to grade subjects' responses, asking them to use their discretion as to whether to accept answers not on the original list. Their inter-rater reliability was high (with an average alpha for the two domains of 0.84) and their confidence in their ratings was high (on average, across the two domains, the coders were moderately to highly confident for 95 percent of the students' answers). The dependent measure is subjects' total number of correct answers to the knowledge identification questions.

Our measures for perceived understanding and perceived ease-of-understanding were adapted from past conceptual modeling research (Burton-Jones and Meso 2006; Gemino 1998). The only difference was that our questions focused on the *information* in the diagrams to ensure that subjects did not think that we were focusing on their ease of understanding the diagram *syntax*.

Experimental Design. We assigned the treatment (type of diagram) as a between-groups variable and the domain (auction or travel) as a within-groups variable. Thus, subjects performed the experimental task twice, once for each domain, and on each occasion they used either a guided or an unguided diagram. We also randomized the order of domains that subjects received.

Procedure. In the preexperiment phase, subjects were given 20 minutes training on OWL and 10 minutes to practice knowledge identification questions on a different domain than those used in the experimental tasks. Subjects then received feedback on their performance in the practice task.

In the experimental phase, subjects were assigned randomly to either the guided or unguided treatment and thus received either a guided or unguided diagram for both domains (auction and travel). They then answered comprehension questions about the diagram, before performing the knowledge identification task for that domain. In keeping with past studies using the transfer task (Gemino 1998; Mayer 2001), the comprehension questions were not a dependent measure, but were simply used to help participants engage with the diagrams. After completing the comprehension questions, participants performed the knowledge identification questions. There was no time limit for this task, but subjects' time was recorded. The sequence was repeated for the second domain (with the order of domains assigned randomly) and thus each subject performed the task twice.

Finally, in the post-experiment phase, subjects received a previously prepared list of acceptable answers to the questions and were allowed to compare their answers to this list and then complete the post-test questionnaire. They were advised that this list of acceptable answers was only a guide, and that the graders may also consider other answers by subjects to be acceptable. To ensure the procedures worked, we ran a pilot study with 22 subjects before the experiment. The results from the pilot test were consistent with the hypotheses, so no major changes were made.

Control Variables. To provide additional evidence that differences between groups stemmed from our treatment rather than from confounds, we obtained data on several control variables: *prior domain knowledge, modeling knowledge, time to perform the task, and order of domains*. Prior domain knowledge is used as a control variable because subjects might try to use their prior knowledge to perform the task rather than using the diagram (Pretz et al. 2003). Likewise, modeling knowledge was measured because subjects with high modeling knowledge may find the tasks easier to perform than subjects with low modeling knowledge. Items for these two variables were adapted from Gemino's (1998)

Table 5. Descriptive Statistics

Variables	Scale	Mean Guided	St. Dev. Guided	Mean Unguided	St. Dev. Unguided	Mean Average	St. Dev. Average
Travel knowledge identification	0–8*	4.04	1.45	2.65	1.14	3.35	1.47
Auction knowledge identification	0–7*	3.63	0.90	2.48	0.94	3.05	1.08
Perceived understanding – F	1–7	4.83	0.78	4.13	0.77	4.48	0.85
Perceived ease-of-understanding – F	1–7	4.52	0.58	3.70	0.65	4.11	0.74
Modeling knowledge	1–7	3.80	1.38	3.82	1.26	3.81	1.31
Travel domain knowledge	1–7	3.50	1.62	3.82	1.04	3.66	1.35
Auction domain knowledge	1–7	2.73	1.48	3.54	1.51	3.13	1.53
Average domain knowledge	1–7	3.12	1.39	3.68	1.16	3.40	1.30
Time (for knowledge identification)	mins.	11.62	1.45	11.95	1.53	11.79	1.48

Notes: Perceived variables: F: responses after feedback

*The knowledge identification questions were open-ended, so the maximum score is undefined. However, the list of correct answers suggests a "practical" maximum of 7 or 8 for each domain.

work. Time was measured because differences in model quality may impact the time required to complete a task (Jarvenpaa and Machesky 1989). Finally, order of domains was used to control for learning effects.

Results

In presenting our results, we first describe our screening of the data and then discuss whether our hypotheses were confirmed.

Data Screening. The descriptive statistics in Table 5 were in line with our expectations. The scores for knowledge identification were low to middling, in line with the challenging nature of the task. The scores for modeling knowledge and prior domain knowledge were also in a middling range, consistent with our sampling strategy. The scores for our dependent variables were always higher in the guided groups than in the unguided groups. In more detailed tests (not shown to conserve space), we examined the normality of each variable and found no major violations. Finally, we checked for outliers, but none affected the results.

Table 6 shows the correlation matrices. Three sets of correlations deserve note. First, in terms of the hypotheses, the treatment was significantly correlated with each dependent measure. Second, in terms of the control variables, the results indicated that "modeling knowledge" was the only control variable significantly related to any of the dependent measures. Third, there was a significant difference in auction domain knowledge between treatments (also evident in Table 5) even though we randomized subjects to groups. However, the correlations in Table 6 indicate that auction domain knowledge did not have a significant effect on any of the outcomes, so although this difference between groups was unexpected, it does not pose a threat to our tests.

For instrument reliability and validity, we first checked the perceived variables. For reliability, we found that one item ("the diagram required lot of mental effort") performed poorly. After removing this item, the scale reliabilities were acceptable in both experiments. Cronbach's alphas for perceived understanding and ease of understanding were 0.88 and 0.85, respectively. In a principal component analysis, the six items loaded highly (> 0.8) on their respective constructs (understanding and ease-of-understanding) and diverged cleanly from each other.

We then checked the reliability and validity of the knowledge identification scores. The reliability of the knowledge identification scores was acceptable, with an average alpha of 0.74. We performed a MANOVA with all the knowledge identification questions as dependent measures to check convergent validity. The p values were less than 0.05 for all questions in both domains, implying a good level of convergent validity because each knowledge identification question behaved similarly. Additional tests using this MANOVA are reported later. Overall, there appeared sufficient evidence at the end of this step to proceed to test the hypotheses.

Test of Hypothesis 1. To test Hypothesis 1, we used ANCOVA for each domain. Subjects' responses to the knowledge identification task were graded in a binary (0/1)

Table 6. Correlation Matrices

	Treatment	Order	Modeling knowledge	Knowledge identification (Auction)	Knowledge identification (Travel)	Perceived understanding (Feedback)	Perceived ease-of-understanding (Feedback)	Time: Auction task	Time: Travel task	Domain knowledge: Auction
Order	-0.18									
Modeling knowledge	-0.01	0.19								
Knowledge identification (Auction)	0.54**	0.02	0.20							
Knowledge identification (Travel)	0.47**	-0.04	0.11	0.82**						
Perceived understanding (Feedback)	0.42**	0.07	0.34**	0.34**	0.35**					
Perceived ease-of-understanding (Feedback)	0.56**	0.00	0.24*	0.31**	0.31**	0.46**				
Time: Auction task	-0.07	0.42*	0.05	-0.09	-0.08	0.09	0.10			
Time- Travel task	-0.02	0.14	-0.10	-0.14	-0.08	-0.03	-0.02	0.65**		
Domain knowledge: Auction	-0.26*	-0.17	0.16	-0.16	-0.09	-0.16	-0.13	-0.15	-0.26	
Domain knowledge: Travel	-0.12	-0.05	0.15	-0.07	-0.08	0.07	0.02	-0.12	-0.23	0.62**

*p < 0.05; **p < 0.01; **Treatment**: 0: Unguided; 1: Guided; **Order**: 0: Travel first; 1: Auction first

fashion. To determine if this method of coding would affect our results, we coded the data in two additional ways to facilitate sensitivity tests. The first step was to ask domain experts to rank all acceptable responses (at most seven for each question). Then, the experts were asked to assess each response in two ways: (1) to discriminate between more/less important answers; and (2) to rank all responses of a subject in terms of importance (using as a guide the ranking of acceptable answers). Next, weighted scores for each response were calculated based each of the methods. For example, if a subject had two responses, one "more" and one "less" important, the weighted score would be $(1 \times 1) + (1 \times 2) = 3$. For the second method, if the individual responses were ranked 3 and 5, the score would be $(1 \times 3) + (1 \times 5) = 8$. Finally, we performed all the tests for Hypothesis 1 with the weighted scores obtained with the two methods. The pattern of results was essentially the same. Thus, we conclude that the results were not sensitive to the way we coded the knowledge identification questions, and in the remainder of this paper, we just use the results from the first (binary) method. The results shown in Table 7 strongly support Hypothesis 1. The levels of explained variance in Table 7 suggest that the treatment had what Cohen (1988) would refer to as a "large" effect.

Tests of Hypotheses 2a and 2b. To test these hypotheses, we ran an ANCOVA for each dependent variable with *treatment* (type of diagram) as the between-groups variable. Table 8 shows the results. The results supported the hypotheses, showing a similar pattern to those for Hypothesis 1.

Overall Test. As a final check on hypotheses, we ran a MANOVA to study the treatment's effect on all three dependent variables together. As Table 9 shows, the treatment had a significant effect on every outcome. Overall, the results strongly support all three hypotheses.

Experiment 2

Given that Experiment 1 showed that our hypotheses could receive strong support when using at least *some* ontologies from practice, the aim of Experiment 2 was to identify precisely *what types* of violations of our guidelines matter most,

Table 7. ANCOVA Results for Knowledge Identification for Each Domain (Hypothesis 1)

Travel Domain			Auction Domain		
Variables	**F**	**Sig. (1-tail)**	**Variables**	**F**	**Sig (1-tail)**
Mod Kn	0.61	0.22	Mod Kn	3.67	0.03*
DKn-TR	0.80	0.19	DKn-AU	0.38	0.27
Time-TR	0.11	0.37	Time-AU	0.46	0.25
Treat	16.03	0.00*	Treat	18.8	0.00*
Adjusted R^2 = 0.20			***Adjusted R^2 = 0.29***		

Key: Dependent variable: Knowledge identification. *Significance at 0.05 level.
Variables: ***Mod Kn***: Modeling knowledge; ***DKn-TR***: Prior domain knowledge of the travel domain; ***DKn-AU***: Prior domain knowledge of the auction domain; ***Time-TR***: Time for the travel task; ***Time-AU***: Time for the auction task; ***Treat***: Treatment (guided versus unguided diagram).

Table 8. ANCOVA Results for Perceived Variables for Both Domains (Hypotheses 2a and 2b)

Perceived understanding *after* feedback (for both domains)			Perceived ease-of-understanding *after* feedback (for both domains)		
Variables	**F**	**Sig. (1-tail)**	**Variables**	**F**	**Sig (1-tail)**
Mod Kn	7.43	0.00*	Mod Kn	3.97	0.02*
DKn	0.00	0.49	DKn	0.05	0.41
Order	0.44	0.26	Order	0.33	0.28
Treat	12.42	0.00*	Treat	24.77	0.00*
Hypothesis 2a: Adjusted R^2 = 0.25			***Hypothesis 2b: Adjusted R^2 = 0.33***		

Key: Dependent variables: Perceived understanding, perceived ease-of-understanding. *Significance at 0.05 level.
Variables: ***Mod Kn***: Modeling knowledge; ***DKn***: Average prior domain knowledge for the two domains; ***Order***: Order of domains (0 = Travel first; 1 = Auction first); ***Treat***: Treatment (guided versus unguided diagrams).

Table 9. MANCOVA Results for All Three Dependent Variables (Hypotheses 1, 2a, and 2b)

Dependent Variable	df	F	Sig. (1-tail)
KnS-TR	54, 1	22.05	0.00*
KnS-AU	54, 1	15.69	0.00*
P-Ease-F	54, 1	24.54	0.00*
P-Und-F	54, 1	11.43	0.00*

*Significance at 0.05 level. **Variables:** ***KnS-TR***: Knowledge identification score on the travel task; ***KnS-AU****: Knowledge identification score on the auction task;* ***P-Ease-F***: Perceived ease-of-understanding (feedback); ***P-Und-F***: Perceived understanding (Feedback) that is, does any violation matter or only some, or some combinations? A secondary aim of Experiment 2 was to obtain perceptual data (for Hypotheses 2a and 2b) both before and after subjects received feedback. In Experiment 1, we obtained this data only *after* subjects received feedback, limiting the conclusions we could draw. In short, this new experiment would enable us to derive more precise conclusions from our results, and thereby allow us to draw more concrete implications for research and practice.

Method

Subjects and Task. The subjects had similar profile as that of Experiment 1. We recruited 100 subjects who were randomly assigned to a treatment. The knowledge identification task used in this experiment was the same as the one used in Experiment 1.

Treatment. The same treatment "use of guided versus unguided ontologies" was used in this experiment. However, we used three versions of unguided ontologies which we discuss in detail below. The ontologies and narratives are in Figures C5 through C12 in Appendix C.

Because our guidelines are for modeling domains, the starting point for creating a guided ontology should be a description of a domain. Accordingly, we began with a narrative description of a domain adapted from the diagrams in Experiment 1, created the guided ontology by modeling the domain according to the guidelines, and created several unguided versions by violating specific guidelines. The violations in the three unguided versions mirrored the three types of violations that we showed earlier in Figure 2.

- Type 1: We created this version by removing all of the interaction classes and modeling the properties of those classes as properties of the interacting classes. For example, properties of the Reservation class (FinalPrice and PenaltyPrice) are modeled as ReservationFinalPrice and ReservationPenaltyPrice of the class Customer. Violating Guideline 1 in this way automatically violates Guidelines 2 through 4 because the interaction classes (e.g., ProposedItinerary and Reservation) no longer exist in this version, so the links between interacting and interaction classes disappear. To connect the interacting classes, we followed the same prefix (ParticipatesIn) used in the other guided versions.

- Type 2: We created this version by removing most of the interacting classes. Because these interacting classes had only one intrinsic property (name), the class name could be modeled as a property of the interaction class. For example, the class TravelAgency is modeled as the property TravelAgencyName in the Reservation and ProposedItinerary classes. Violating Guideline 1 in this way automatically violates Guidelines 3 and 4 because the corresponding links between interacting and interaction classes are lost.

- Type 3: We created this version by using the Type 2 violation and, additionally, violating Guideline 2 by modeling some mutual properties of the interaction classes as properties of the interacting classes instead. For example, the FinalPrice of the Reservation class is modeled as ReservationFinalPrice in the Customer class. Thus, this type of unguided diagram violates all of the guidelines. Of the three types of unguided diagrams in Experiment 2, this type is the most similar to the unguided diagrams in Experiment 1, which likewise failed to show some interacting classes and failed to model mutual properties in accordance with our guidelines.

In addition to creating the unguided and guided diagrams differently in Experiment 2 than in Experiment 1, we handled the issue of informational equivalence differently. According to Burton-Jones et al. (2009), if applying a theoretically informed treatment results in differences in information content, researchers should not attempt to correct for informational inequivalence. Following this recent study, we made sure that the only differences between the guided and unguided diagrams in Experiment 2 stemmed from our application of the theoretically informed guidelines; we made no adjustments to the diagrams in terms of informational equivalence. This was in keeping with our aim in Experiment 2, which was to ensure maximal experimental control.

Dependent and Control Variables. The same dependent and control variables were used in this experiment. The same coders graded the responses of the knowledge identification questions. Their inter-rater reliability was high (with an average alpha for the two domains of 0.83) and their confidence in their ratings was high (on average, across the two domains, the coders were highly confident for 93 percent of the responses).

Experimental Design. The only difference in the design of the experiments related to the differences in diagrams. The treatment in this experiment used four groups (one guided, three unguided) as compared to two groups (one guided, one unguided) in Experiment 1. This also led to a difference in the sample size of the studies. We planned a sample size of 100 students for four groups for this experiment.

Table 10. Descriptive Statistics

Variables	Scale	Mean Guided	St. Dev. Guided	Mean Unguided	St. Dev. Unguided	Mean Average	St. Dev. Average
Travel knowledge identification	0–8*	3.55	1.55	2.96	1.32	3.11	1.40
Auction knowledge identification	0–7*	3.29	1.30	2.80	1.34	2.93	1.34
Perceived understanding – N	1–7	4.73	0.93	4.56	1.08	4.61	1.04
Perceived understanding – F	1–7	4.83	0.96	4.38	1.04	4.50	1.04
Perceived ease-of-understanding – N	1–7	4.52	0.87	4.09	1.09	4.21	1.05
Perceived ease-of-understanding – F	1–7	4.81	0.72	4.24	0.75	4.38	0.78
Modeling knowledge	1–7	3.83	0.81	4.03	1.10	3.98	1.03
Travel domain knowledge	1–7	3.77	1.32	3.82	1.30	3.81	1.30
Auction domain knowledge	1–7	2.63	0.90	2.72	1.15	2.70	1.10
Average domain knowledge	1–7	3.20	0.91	3.27	0.87	3.25	0.88
Time (for knowledge identification)	mins.	10.65	1.56	10.96	1.67	10.88	1.64

Notes: Perceived variables: F: responses after feedback; N: responses before feedback.
*The knowledge identification questions were open-ended, so the maximum score is undefined. However, the list of correct answers suggests a practical maximum of 7 or 8 for each domain.

Procedure. To test that the procedures worked, we conducted a pilot study with 18 subjects. As the results were consistent with expectations, no changes were made prior to the full experiment. The only aspect of the procedure that differed between Experiments 1 and 2 concerned the post-experimental phase. In both experiments, subjects were given the list of correct answers for the knowledge identification tasks to help them gauge how well they had understood the diagrams *before* giving their ratings on the perceptual measures (for perceived understanding and perceived ease-of-understanding). Based on prior research, we expected that this would increase the likelihood that subjects' perceptions would be accurate (Cahn and Frey 1989). An implication of this procedure is that the construct we measured is actually "perceptions with feedback" rather than perceptions in general. Thus, in this experiment, we provided subjects with the questions for the perceived variables twice: both before and after receiving feedback. In this way, we measured both "perceptions without feedback" and "perceptions with feedback" in Experiment 2.

Results. In presenting our results, we first describe our screening of the data and then discuss whether our hypotheses were confirmed.

Data Screening. Table 10 shows the descriptive statistics, which were similar to those in Experiment 1. The main difference is that in Experiment 2 we had two measures of each perceived dependent variable. As Table 10 shows, the differences between groups in perceived understanding and perceived ease-of-understanding were also always greater after feedback than before it (listed as "F" and "N" respectively in Table 10).

Table 11 shows the correlation matrices. The treatment was significantly correlated with only a subset of the dependent measures. Consistent with the descriptive statistics, the relationship between the treatment and the perceptual measures was significant only *after* feedback had been provided. All of the control variables (modeling knowledge, prior domain knowledge, order of tasks, and time taken) had significant effects, with different effects on different dependent measures.

For instrument reliability and validity, we first examined the results for the perceptual measures and then the knowledge identification scores. For perceived understanding and ease-of-understanding, the reliability values were adequate (Cronbach's alpha for perceived understanding with feedback and without it were 0.93 and 0.93 respectively and for perceived ease-of-understanding with feedback and without it were 0.69 and 0.87 respectively). In terms of construct validity, however, the items for perceived understanding and ease-of-understanding failed to discriminate, loading mainly on one factor. For the measures with *no* feedback, five items loaded highly (> 0.7) on one factor and one item cross-loaded on two factors (0.5 to 0.7). For the measures *with* feedback, all six items loaded highly (> 0.7) on one factor. We found the same pattern of results in the perceptual measures both with and without feedback. Because our hypotheses are the same for understanding and ease-of-understanding, we decided to proceed to our hypothesis tests, but the lack of discriminant

Table 11. Correlation Matrices

	Treatment	Order	Modeling knowledge	Knowledge identification (Auction)	Knowledge identification (Travel)	Perceived understanding		Perceived ease-of-understanding		Time: Auction task	Time: Travel task	Domain knowledge: Auction
						No feedback	Feedback	No feedback	Feedback			
Order	0.00											
Modeling knowledge	-0.09	0.04										
Knowledge identification (Auction)	0.06	0.20*	0.19*									
Knowledge identification (Travel)	0.18*	-0.01	0.06	0.65**								
Perceived understanding (no feedback)	0.07	0.02	0.23*	0.10	0.01							
Perceived understanding (feedback)	0.19*	-0.04	-0.03	0.16	0.16	0.55**						
Perceived ease-of-understanding (no feedback)	0.16	0.02	0.12	0.07	0.06	0.70**	0.42**					
Perceived ease-of-understanding (feedback)	0.24**	0.00	-0.05	0.21*	0.08	0.55**	0.54**	0.54**				
Time: Auction task	0.03	0.54**	0.06	0.31**	0.04	0.11	0.03	0.01	0.11			
Time- Travel task	-0.15	-0.32**	0.05	0.17	0.29**	-0.09	-0.11	-0.14	0.02	-0.08		
Domain knowledge: Auction	-0.04	0.00	0.07	0.15	0.18*	-0.07	0.05	-0.18*	-0.13	-0.04	0.18*	
Domain knowledge: Travel	-0.02	0.08	0.16	0.07	0.04	0.10	0.06	0.12	-0.03	0.02	-0.00	0.08

*p < 0.05; **p < 0.01; **Treatment:** 0: Unguided; 1: Guided; **Order:** 0: Travel first; 1: Auction first

validity between these variables should be borne in mind when interpreting our results. We return to this issue later.

For the knowledge identification scores, the reliability values were acceptable (average alpha = 0.80). We ran a MANOVA with all of the knowledge identification questions as dependent measures to check convergent validity. In the travel domain, the results for all of the questions were in the expected direction and significant; in the auction domain, the results for all of the questions were again in the expected direction but only one of three was significant. Therefore, it appeared that there was reasonable convergent validity, in that the questions behaved similarly, although the pattern was less strong than in Experiment 1. While we keep this issue in mind, we felt satisfied that, overall, the reliability and validity of our data were adequate to proceed to test the hypotheses.

Tests of Hypotheses. In this experiment we had three unguided groups. Based on our theory, we did not have a strong expectation of differences among the three unguided groups except that the results would likely be stronger for the unguided groups receiving the Type 1 and Type 3 violations, because they violated all four guidelines whereas the Type 2 condition violated only three. To explore what differences occurred, we compared the means for each guided/unguided group (see Table 12).

The results indicate that the differences for all three unguided groups were consistent with our hypotheses, but the differences were greatest for the group receiving the Type 3 violation. Some of the results were also significant in the group receiving the Type 1 violation. Moreover, of the three unguided groups, the results from the group receiving the Type 3 violation were the closest to the results from the average of all three unguided groups.

The results in Table 12 suggest that the Type 3 violations were the most critical of the ones we included in our design.

Table 12. Dependent Measures by Types of Violations

Unguided diagram	N	Dependent variable	Means (Std. Dev.)		df	Mean Square	F	Sig.
			Guided	*Unguided*				
Type 1 violation	26 (guided) 27 (unguided)	KnS-TR	3.6 (1.6)	3.2 (1.1)	51, 1	1.89	1.05	0.16
		KnS-AU	3.3 (1.3)	3.2 (1.2)	51, 1	0.24	0.16	0.34
		KnS-Avg	3.4 (1.3)	3.2 (1.0)	51, 1	0.87	0.65	0.21
		P-Und-N	4.7 (0.9)	4.4 (1.1)	51, 1	1.60	1.40	0.12
		P-Und-F	4.8 (0.9)	4.4 (0.9)	51, 1	3.15	3.35	0.03*
		P-Ease-N	4.7 (0.9)	3.9 (1.1)	51, 1	7.75	6.85	0.00*
		P-Ease-F	4.9 (0.8)	4.4 (0.7)	51, 1	3.49	5.90	0.00*
Type 2 violation	26 (guided) 19 (unguided)	KnS-TR	3.6 (1.6)	3.3 (1.7)	43, 1	0.91	0.35	0.28
		KnS-AU	3.3 (1.3)	2.7 (1.5)	43, 1	3.64	1.93	0.08
		KnS-Avg	3.4 (1.3)	3.0 (1.5)	43, 1	2.05	1.08	0.15
		P-Und-N	4.7 (0.9)	4.7 (1.2)	43, 1	0.00	0.00	0.48
		P-Und-F	4.8 (0.9)	4.5 (1.3)	43, 1	1.15	0.90	0.17
		P-Ease-N	4.6 (0.9)	4.7 (1.1)	43, 1	0.08	0.07	0.40
		P-Ease-F	4.8 (0.8)	4.5 (1.0)	43, 1	1.89	2.18	0.07
Type 3 violation	26 (guided) 28 (unguided)	KnS-TR	3.6 (1.6)	2.6 (1.2)	52, 1	13.58	7.40	0.00*
		KnS-AU	3.3 (1.3)	2.5 (1.4)	52, 1	8.26	4.57	0.02*
		KnS-Avg	3.4 (1.3)	2.5 (1.1)	52, 1	10.76	7.51	0.00*
		P-Und-N	4.7 (0.9)	4.6 (0.9)	52, 1	0.13	0.16	0.34
		P-Und-F	4.8 (0.9)	4.3 (0.9)	52, 1	3.53	4.01	0.02*
		P-Ease-N	4.7 (0.9)	4.4 (0.9)	52, 1	1.28	1.56	0.11
		P-Ease-F	4.9 (0.8)	4.5 (0.6)	52, 1	1.98	3.56	0.03*
Average	26 (guided) 74 (unguided)	KnS-TR	3.6 (1.6)	3.0 (1.4)	98, 1	6.74	3.53	0.03*
		KnS-AU	3.3 (1.3)	2.9 (1.3)	98, 1	4.68	2.63	0.06
		KnS-Avg	3.4 (1.3)	2.8 (1.2)	98, 1	5.66	3.75	0.03*
		P-Und-N	4.7 (0.9)	4.6 (1.1)	98, 1	0.54	0.49	0.24
		P-Und-F	4.8 (0.9)	4.4 (1.1)	98, 1	3.98	3.79	0.03*
		P-Ease-N	4.6 (0.9)	4.3 (1.1)	98, 1	2.69	2.44	0.06
		P-Ease-F	4.9 (0.8)	4.4 (0.8)	98, 1	3.71	5.85	0.00*

*Significance at 0.05. **Variables**: ***KnS-TR***: Knowledge identification score (travel); ***KnS-AU***: Knowledge identification score (auction); ***KnS-Avg***: Knowledge identification score (average of auction and travel); ***P-Und-N***: Perceived understanding (no feedback); ***P-Und-F***: Perceived understanding (feedback); ***P-Ease-N***: Perceived ease-of-understanding (no feedback); ***P-Ease-F***: Perceived ease-of-understanding (feedback).

As we noted earlier, this was the type of violation that was most similar to the type of violation used in Experiment 1. To determine if it truly led to significant effects, we ran the same tests as we did for Experiment 1 for this condition. We report the results of these tests in the following subsections. We also report for each hypothesis whether the results differed when comparing the guided group to the other unguided groups (i.e., Types 1 and 2).

Hypothesis 1. To test Hypothesis 1, we used a separate ANCOVA for each domain (see Table 13). The results supported Hypothesis 1, indicating that the difference between groups for the Type 3 violation had what Cohen (1988) referred to as a "medium" effect. Although not shown in this table, the same tests for the other unguided groups proved insignificant.

Hypotheses 2a and 2b. Table 14 shows the ANCOVA results for each dependent variable. As the table shows, the treatment had a significant effect on the perceptual measures *after* (but not before) feedback was given, with a small-to-medium effect size. Although not shown in the table, the

Table 13. ANCOVA Results for Knowledge Identification for Each Domain (Hypothesis 1)

Travel Domain			Auction Domain		
Variables	**F**	**Sig. (1-tail)**	**Variables**	**F**	**Sig. (1-tail)**
Mod Kn	0.11	0.37	Mod Kn	1.44	0.12
DKn-TR	0.12	0.37	DKn-AU	1.13	0.15
Time-TR	3.75	0.03*	Time-AU	8.10	0.00*
Treat	7.88	0.00*	Treat	4.03	0.03*
Adjusted R^2 = 0.11			***Adjusted R^2 = 0.18***		

Key: Dependent variable: Knowledge identification. *Significance at 0.05 level.
Variables: ***Mod Kn***: Modeling knowledge; ***DKn-TR***: Prior domain knowledge of the travel domain; ***DKn-AU***: Prior domain knowledge of the auction domain; ***Time-TR***: Time for the travel task; ***Time-AU***: Time for the auction task; ***Treat***: Treatment (guided versus unguided diagram).

Table 14. ANCOVA Results for Perceived Variables for Both Domains (Hypotheses 2a, 2b)

Perceived understanding *before* feedback (for both domains)			Perceived ease-of-understanding *before* feedback (for both domains)		
Variables	**F**	**Sig. (1-tail)**	**Variables**	**F**	**Sig. (1-tail)**
Mod Kn	4.39	0.02*	Mod Kn	7.88	0.00*
DKn	1.21	0.14	DKn	0.02	0.44
Order	0.04	0.43	Order	0.41	0.26
Treat	0.32	0.28	Treat	2.02	0.08
Hypothesis 2a: Adjusted R^2 = 0.04			***Hypothesis 2b: Adjusted R^2 = 0.10***		
Perceived understanding *after* feedback (for both domains)			**Perceived ease-of-understanding *after* feedback (for both domains)**		
Variables	**F**	**Sig. (1-tail)**	**Variables**	**F**	**Sig. (1-tail)**
Mod Kn	0.04	0.42	Mod Kn	0.00	0.48
DKn	3.29	0.04*	DKn	1.18	0.14
Order	1.33	0.12	Order	1.00	0.16
Treat	4.56	0.02*	Treat	3.21	0.04*
Hypothesis 2a: Adjusted R^2 = 0.07			***Hypothesis 2b: Adjusted R^2 = 0.03***		

Key: Dependent variables: Perceived understanding, perceived ease-of-understanding. * Significance at 0.05 level.
Variables: ***Mod Kn***: Modeling knowledge; ***DKn***: Average prior domain knowledge for the two domains; ***Order***: Order of domains (0 = Travel first; 1 = Auction first); ***Treat***: Treatment (guided versus unguided diagrams).

Table 15. MANOVA Results for All Three Dependent Variables (Hypotheses 1, 2a, 2b)

Dependent Variable	df	F	Sig. (1-tail)
KnS-TR	52, 1	7.41	0.00*
KnS-AU	52, 1	4.56	0.02*
P-Ease-F	52, 1	3.56	0.03*
P-Und-F	52, 1	4.02	0.03*

*Significance at 0.05 level. ***Variables:*** **KnS-TR**: Knowledge identification score on the travel task; **KnS-AU**: Knowledge identification score on the auction task; **P-Ease-F**: Perceived ease-of-understanding (feedback); **P-Und-F**: Perceived understanding (feedback).

same tests for the unguided Type 2 violation group proved insignificant. For the unguided Type 1 violation group, the treatment had a significant effect on all the perceptual measures except perceived understanding (no feedback), mirroring the pattern of results shown earlier in Table 12.

Overall Test. Finally, we ran a MANOVA on all three dependent variables together using this one unguided group (the Type 3 violation). The results mirrored those of Experiment 1. In this test, we only included the perceptual measures *after* feedback was given. Thus, Table 15 shows the *one* type of violation, and the *one* type of perceptual measure, that exhibited consistently significant effects. For the other types of violations, and for the perceptual measures before feedback, the results showed less differences (and sometimes, no significant differences). Overall, the results seem to complement Experiment 1's results because, of the three types of violation in Experiment 2, the type that led to significant differences was most like the type of violations in the unguided diagram in Experiment 1.

Experiment 3

We ran Experiment 3 to confirm the cognitive processes purported in our theory. We had theorized that when individuals use representations that *lack* fit with their tasks, they need to reorganize the representation in their mind so that the information needed to perform the task becomes clearer. Because reorganizing a representation takes effort, and may not be done effectively, this should have observable effects. Specifically, compared to individuals with guided diagrams, individuals with unguided diagrams should differ observably in three ways:

- *Breakdowns*: Individuals with unguided diagrams should suffer more cognitive breakdowns—failures in completing lines of thought—because the additional effort to reorganize the model may exceed their information processing capacity and/or because they fail to reorganize the model in their minds effectively.

- *Engaging with relevant concepts*: Individuals with unguided diagrams should engage less often with relevant concepts (such as interacting classes relevant for their knowledge identification task) because they may fail to reorganize the representation effectively.

- *Performance*: Individuals with unguided diagrams should perform worse in the task because of either of the previous two reasons (i.e., more breakdowns and/or less engagement).

While Experiment 2 obtained evidence of performance, Experiment 3 sought evidence of all three effects, as well as the link from the cognitive effects (breakdowns and engagement) to performance.

Method

Experiment 3 mirrored Experiment 2 except that we used only one control condition: the Type 3 violation. Ten subjects were recruited. They had a similar profile to those in both of the prior experiments and were graduate students of a southern U.S. university. Five received the guided diagram and five the unguided diagram (Type 3 violation), based on random assignment. Performance in the knowledge identification task was graded as in the prior experiments. The materials and procedure were also the same as those in Experiment 2, except that each subject was asked to "think aloud" (verbalize) during the tasks and recordings were taken. Two independent raters then coded each subject's verbal protocol (interrater reliability = 0.87) for

- *Breakdowns*. As in Vessey and Conger (1994), breakdowns were identified by comments that indicated that a line of thought failed. We identified two types: implicit breakdowns, in which subjects experienced a breakdown but did not say so explicitly, and explicit breakdowns, in which subjects stated that a line of thought failed. Examples include

  – "…can the auction house have a uhmm…. [pause, then changes line of reasoning] Auction item is not a prepaid thing" (implicit breakdown)

  – "I don't get any clue from the diagram" (explicit breakdown)

- *Verbalization of interacting classes.* The raters coded each time subjects mentioned the interacting classes in the guided diagrams that were shown merely as properties in the unguided diagrams. Examples include mentioning "service provider" in the travel domain and "auction house" in the auction domain.

Table 16 shows the results, which confirmed our expectations: on average, subjects in the guided group suffered fewer breakdowns (implicit and explicit), mentioned interacting classes more often, and performed better. Although not shown in Table 16, we also calculated nonparametric correlations (Spearman's rho) among the variables. These results showed that the treatment had a significant effect on total

Table 16. Results from Protocol Analysis

	Number of breakdowns			Verbalization of interacting classes	Knowledge identification score
	Implicit	Explicit	Total		
UG1	10	1	11	3.5	9.0
UG2	11	1	12	9.0	7.0
UG3	6	3	9	7.0	8.5
UG4	12	1	13	3.0	5.0
UG5	8	0	8	10.0	8.0
Average	**9.4**	**1.2**	**10.6**	**6.5**	**7.5**
G1	8	0	8	8.0	10.0
G2	10	0	10	12.5	12.0
G3	2	0	2	4.5	8.0
G4	5	0	5	10.0	12.5
G5	3	0	3	5.5	11.5
Average	**5.6**	**0**	**5.6**	**8.1**	**10.8**

Key: UG: Unguided; G: Guided. For brevity, the table shows the average values for the two domains (auction and travel). The pattern of results is similar in each domain.

breakdowns (rho = -.70) and performance (rho = .70). The effect on verbalizations, while not significant (rho = .28), was in the expected direction. The results also supported the link from cognition (breakdowns and engagement) to performance, as breakdowns and verbalizations both had a significant effect on performance (rho = -.45, and .47, respectively). These results seem to provide quite strong support for the line of reasoning purported in our theory.

In addition to confirming our theory, the results offer a reason why the perceptual measures in Experiment 2 were significant only after feedback was given. Specifically, Table 16 shows that subjects experienced many implicit but few explicit breakdowns. Explicit breakdowns should be strongly linked to perceptions because the individual is aware of the problem. In contrast, because people have a limited ability to assess their own cognitive states (Wilson and Dunn 2004), those who experience implicit breakdowns may not be aware of the difficulties they experience at that moment. We surmise that these subjects only realized the difficulties they faced when they had to reconcile their experiences with feedback on their performance. Overall, the results of the protocol analysis seem to confirm and complement those of the other two experiments.

Discussion

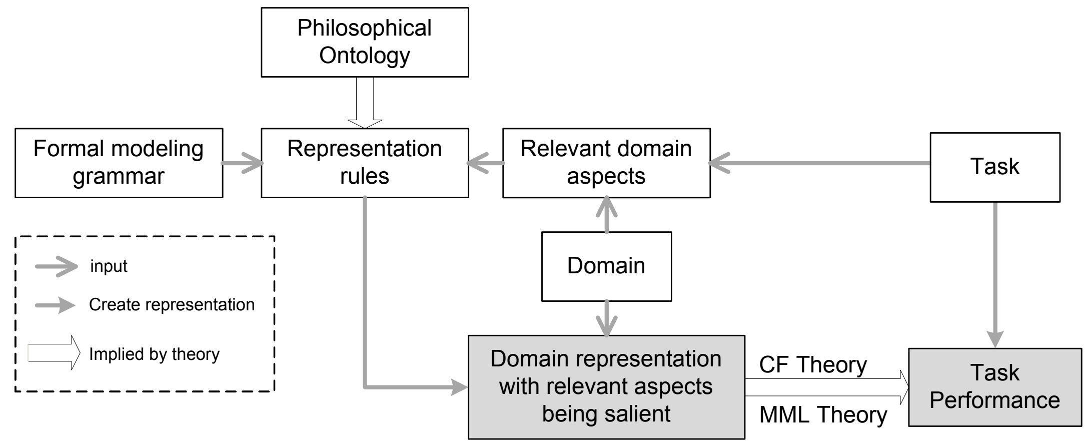
The paper breaks new ground in several ways. We summarize its contributions in the following sections before outlining its limitations and its implications for future research.

Contributions to Theory

Our work contributes theoretically in two main ways. First, it highlights the importance of knowledge identification in the KMS context, defines the concept precisely, and distinguishes it from related constructs such as problem solving. Second, it shows how visual ontologies can be used to support knowledge identification and how theories of ontology and cognition can be used in combination to improve the expressiveness of these ontologies.

On a general level, our study contributes to what Gregor (2006) calls "theory for prescription." In our case, this refers to using ontological and cognitive theories to guide the design of visual ontologies for a specific task. Although the notion of providing ontologies to help people learn a domain and identify search terms has existed in the information retrieval field for some time, there has been no specific guidance for designing ontologies to support knowledge identification. In fact, although there are many *generic* guidelines for designing ontologies (Gomez Perez et al. 2004), we are not aware of any guidelines designed to support other *specific* tasks.

Based on the results of our study, we believe the approach we have used can and should be generalized to other cases where a formal modeling grammar (which in our case was OWL, but could be any other grammar, UML being one) is used to provide users with a representation of a domain for the purpose of performing a task related to that domain. Figure 3 illustrates the general approach. As the figure shows, cognitive fit (CF) theory and multimedia learning (MML) theory



Notes: CF: Cognitive Fit; MML: Multimedia Learning
Shaded boxes indicate independent and dependent variables.

Figure 3. An Approach to Creating Representations with Ontologically Informed Fit

both predict that task performance will improve when the domain is presented in a way that fits the task. This implies that aspects of the domain that are most relevant to the task—what Figure 3 terms the "relevant domain aspects"—should be made salient in the representation. These aspects are determined by the nature of the domain and the task. The domain will ultimately be represented by a script created with a formal grammar (a modeling technique). Many scripts might exist. This is where principles from philosophical ontology can provide guidance as to how the formal modeling grammar can be used to make the relevant domain aspects more salient in the script. We refer to this guidance in Figure 3 as "representation rules." In short, the approach we have followed is a method for creating representations that have *ontologically informed fit* for a given task.

While we demonstrated the benefit of achieving ontologically informed fit to one type of task—knowledge identification—the approach should work equally well in other types of tasks in which scripts are created with a formal grammar to represent a domain. For example, consider the domain of new product development. In this domain, a relevant aspect for many tasks (e.g., costing and production planning) is understanding product composition. Following Figure 3, we could refer to ontological theories to determine what aspects to make salient in this context. Bunge's ontology, for example, emphasizes the importance of "emergent properties" of composites. Thus, we could suggest highlighting these emergent properties when representing composites in the script.

Overall, our research serves as a call for more task specificity in the creation of visual representations and as a proposal to use ontological theories to guide such representations. By using an ontological theory in concert with cognitive fit theory and multimedia learning theory, as we have done, we believe that researchers can develop more specific theory-based prescriptions for the creation of representations. Interestingly, in the conceptual modeling field, research using cognitive fit theory (e.g., Agarwal et al. 1996; Khatri et al. 2006) and research using ontological theory (e.g., Bodart et al. 2001; Gemino and Wand 2005) have developed quite independently. Our study illustrates how the two approaches complement each other, an idea that has perhaps been overlooked for too long.

Contributions to Methods

Methodologically, the paper broke new ground in several ways. In terms of its approach, we showed how researchers could use a combination of experiments to strike a balance between empirical precision and empirical realism and showed how a follow-up protocol analysis could provide additional evidence about the process by which a treatment has effects. In terms of instrumentation, we developed a way to operationalize knowledge identification by asking subjects to identify questions needed to create procedures to attain goals. We also improved instruments that had been used in the past to measure individuals' perceptions of diagrams (in studies of conceptual modeling) by focusing the measures on subjects' understanding of the *information* in the diagrams rather than the *syntax*. Finally, we examined the effect of giving feedback to subjects before obtaining their perceptions, finding that perceptions calibrated more accurately with actual performance after feedback had been provided.

Contributions to Practice

The study also has several practical implications. Like Rao and Osei-Bryson (2006), we suggest that end users could benefit from having access to visual ontologies when interacting with knowledge repositories, such as KMSs or the Web. Such visual ontologies could help individuals learn about the domain, and thereby enable them to identify what knowledge to search for in the KMS. Designers need to pay attention to how they implement visual ontologies to support the use of knowledge repositories. The results of our experiments indicate that our guidelines can be helpful in the development of visual ontologies to support knowledge identification.

More generally, the study points out the benefits that can arise from careful analysis of task-relevant aspects of domains and consideration of how these aspects can be made salient in task supporting scripts. The results also indicate how the use of philosophical ontologies to guide modeling can provide practical benefits.

Limitations

The limitations of our study can be understood with reference to the traditional criteria for validity. In terms of *internal validity*, a challenge could be raised regarding the way we dealt with informational equivalence. Specifically, we corrected for informational inequivalence in Experiment 1 by adding terms back to the unguided diagrams. If these added terms confused subjects, this could have created a difference in the results across groups that would not have been due to our treatment, thus threatening internal validity. While this might have been possible, we do not consider it to be a major concern for two reasons. First, adding these terms to the unguided diagrams should have reduced rather than increased the difference in the results in Experiment 1, because this procedure made the terms in the guided and unguided groups more similar. Second, the overall pattern of results was the same in both experiments, and no terms were added to the unguided diagrams in Experiment 2, so we believe that general conclusions can be drawn safely from the experiments.

In terms of *construct validity*, the items for perceived understanding and perceived ease-of-understanding failed to discriminate in Experiment 2. This might have been due to method bias, since the measures were close to each other on the questionnaire and had similar wording (e.g., "I found the information represented in the diagrams easy to interpret" and "I grasped all the information represented in the diagram"). To determine if this was the case, our experiment could be replicated with the measures for each construct separated more from each other on the questionnaire or separated in time. To some extent, however, the lack of discrimination could be substantive and may not be a serious problem, because we expect the two perceptual constructs to be closely connected in individuals' minds, and our hypotheses are the same for both. Nonetheless, future research could address the issue. When doing so, it would be useful to measure these variables for *each* domain, instead of only once at the conclusion of the experiment, as we did.

Our study's *external validity* could be challenged because we used laboratory experiments with student subjects rather than working with real users. However, this practice is typical in the early stages of research (Calder et al. 1981), and we maintained some realism by using diagrams from practice in Experiment 1. Moreover, we believe that the students who participated in our experiments were reasonable proxies for our target population, in that they are individuals who are somewhat familiar with a domain, with learning from diagrams, and can use systems (such as the Web or a KMS) when searching for knowledge. A more relevant threat to external validity is that our experiments examined domains in which users had a *moderate* level of prior knowledge. This might be a realistic assumption, as usually users who search for knowledge would have some notion of the domain. However, future research can be conducted with users with a wider range of prior domain knowledge (ranging from novices to experts) to determine the extent to which our guidelines can apply broadly in practice.

Finally, in terms of *statistical conclusion validity*, several results in Experiment 2 were in the same direction posed by our hypotheses, but the results were not significant, possibly indicating a potential Type 2 error. However, although a larger sample size would have increased the chance of achieving statistically significant results, the practical effect sizes for these differences would still have been low. One possible reason is that the diagrams used in Experiment 2, while being carefully design to include controlled violations of the guidelines, were simpler than the example borrowed from practice in Experiment 1. Therefore, we believe that the overall pattern of results is still meaningful.

Future Research

Several future research opportunities emerge from this study. One direction would be to determine why only one of the three unguided groups in Experiment 2 had strong results. At this stage, we suspect that this was due to the number of types of violations in the different conditions. Specifically, *one* type of change each was made in the Type 1 and Type 2 violations (interaction classes were lost in the Type 1 violation, and mutual properties were misplaced in the Type 2 violation), but *two* types of changes were made in the Type 3 violation (interacting classes were lost and mutual properties were misplaced). Perhaps recovering the true meaning of diagrams is more difficult when they have more types of violations. This would be an important result if future research can confirm it because the result would suggest that designers have some leeway in the extent to which they must comply with modeling guidelines.

Another direction for future research is to increase the practicality of our guidelines. In terms of diagram *creation*, researchers could examine whether analysts can create domain ontologies more efficiently and effectively when they have access to (and/or training in) our guidelines than when they lack access (and/or training). In terms of diagram *interpretation* and *use*, researchers could create a mock-up KMS and implement visual ontologies in the interface to test if the diagrams have the same effect as they did in our pencil-and-paper tasks.

Future research might also extend the scope of our work. For example, researchers could extend the scope of the tasks examined in our study by examining the benefit of our guidelines for problem-solving tasks in addition to knowledge identification tasks. As we noted earlier, we expect that our guidelines would assist both types of tasks. Researchers could also extend the scope of the ontological theories and languages used in our study. We had good reasons for selecting Bunge's ontology and OWL, but the general principle examined in our research—that philosophical ontologies can be used to improve the design of formal domain ontologies—needs to be tested across a wider range of philosophical ontologies, ontological languages, and task types.

Finally, our study represents an attempt to help workers identify the knowledge they need to perform their work tasks. This is an important and difficult challenge that has received little research to date. We hope that future research will identify additional ways to address it and thereby help workers reap the true benefits offered by KMSs and other sources of knowledge at work.

Acknowledgments

We thank participants in research seminars at the University of British Columbia and Texas A&M International University for their comments on earlier versions of the paper. For help with our data collection and coding, we especially thank Kafui Monu and Sase Singh. We also thank Nancy Talbert and Ashley Serl for expert editing. Our SE, AE, and reviewers gave many valuable suggestions that helped us improve the paper. The research was supported by funds from the Social Sciences and Humanities Research Council of Canada, the Natural Sciences and Engineering Council of Canada, and a University Resource Grant from Texas A&M International University.

References

Agarwal, R., Sinha, A. P., and Tanniru, M. 1996. "Cognitive Fit in Requirements Modeling: A Study of Object and Process Methodologies," *Journal of Management Information Systems* (13:2), pp. 137-164.

Angeles, P. 1981. *Dictionary of Philosophy*, New York: Harper Perennial.

Ashcraft, M. H. 2002. *Cognition* (3rd ed.), Upper Saddle River, NJ: Prentice Hall.

Belkin, N. J., Oddy, R. N., and Brooks, H. M. 1982. "ASK for Information Retrieval. Part 1: Background and Theory," *Journal of Documentation* (38:2), pp. 61-71.

Bera, P., Krasnoperova, A., and Wand, Y. 2010. "Using Ontology Languages for Conceptual Modeling" *Journal of Database Management* (21:1), pp. 1-28.

Blosch, M. 2001. "Pragmatism and Organizational Knowledge Management," *Knowledge and Process Management* (8:1), pp. 39-47.

Bodart, F., Patel, A., Sim, A., and Weber, R. 2001. "Should Optional Properties Be Used in Conceptual Modeling? A Theory and Three Empirical Tests," *Information Systems Research* (12:4), pp. 383-405.

Bunge, M. 1977. *The Treatise on Basic Philosophy: Ontology* (Volume 3), New York: D. Reidel Publishing.

Burton-Jones, A., and Meso, P. 2006. "Conceptualizing Systems for Understanding: An Empirical Test of Decomposition Principles in Object-Oriented Analysis," *Information Systems Research*, (17:1), pp. 38-60.

Burton-Jones, A., Wand, Y., and Weber, R. 2009. "Guidelines for Empirical Evaluations of Conceptual Modeling Grammars," *Journal of the Association for Information Systems* (10:6), pp. 495-532.

Burton-Jones, A., and Weber, R. 1999. "Understanding Relationships with Attributes in Entity-Relationship Diagrams,"in *Proceedings of the 20th International Conference on Information Systems*, P. De and J. I. DeGross (eds.), Charlotte, NC, pp. 214-228.

Cahn, D. D., and Frey, L. R. 1989. "Behavioral Impressions Associated with Perceived Understanding," *Perceptual and Motor Skills* (69), pp. 1299-1302.

Calder, B. J., Phillips, L. W., and Tybout, A. M. 1981. "Designing Research for Application," *Journal of Consumer Research* (8), pp. 197-207.

Chisholm, R. M. 1996. *A Realistic Theory of Categories: An Essay on Ontology*, Cambridge, UK: Cambridge University Press.

Cohen, J. 1988. *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.), Hillsdale, NJ: Lawrence Earlbaum Associates.

Daconta, M. Obrst, L., and Smith, K. 2003. *The Semantic Web: The Future of XML, Web Services, and Knowledge Management*, New York: Wiley.

Davies, J., Weeks, R., and Krohn, R. 2002. "QuizRDF: Search Technology for the Semantic Web," in *Proceedings of the Workshop on Real World RDF and Semantic Web Applications, 11th International World Wide Web Conference*, Honolulu, HI.

Evermann, J., and Wand, Y. 2005. "Ontology Based Object-Oriented Domain Modeling: Fundamental Concepts," *Requirements Engineering Journal* (10:2), pp. 146-160.

Fensel D. 2003. *Ontologies: A Silver Bullet for Knowledge Management and E-Commerce*, Berlin: Springer Verlag.

Fliedl, G., Kop, C., and Vohringer, J. 2010. "Guideline Based Evaluation and Verbalization of OWL Class and Property Labels" *Data and Knowledge Engineering* (69:4), pp. 331-342.

Fonseca, F. 2007. "The Double Role of Ontologies in Information Science Research," *Journal of the American Society for Information Science and Technology* (58:6), pp. 786-793.

Ford, N. 2004. "Modeling Cognitive Processes in Information Seeking: From Popper to Pask," *Journal of the American Society for Information Science and Technology* (55:9), pp. 769-782.

Gallupe, B. 2001. "Knowledge Management Systems: Surveying the Landscape," *International Journal of Management Reviews* (3:1), pp. 61-77.

Gemino, A. 1998. *Comparing Object Oriented with Structured Analysis Techniques in Conceptual Modeling,* Unpublished Doctoral Dissertation, University of British Columbia.

Gemino, A., and Wand, Y. 2004. "A Framework for Empirical Evaluation of Conceptual Modeling Techniques," *Requirements Engineering* (9:4), pp. 248-260.

Gemino, A., and Wand, Y. 2005. "Complexity and Clarity in Conceptual Modeling: Comparison of Mandatory and Optional Properties," *Data and Knowledge Engineering* (55), pp. 301-326.

Gomez-Perez, A., Fernandez-Lopez, M., and Corcho, O. 2004. *Ontological Engineering: With Examples for the Area of Knowledge Management, E-commerce and the Semantic Web*, London: Springer-Verlag Limited.

Gregor, S. 2006. "The Nature of Theory in Information Systems," *MIS Quarterly* (30:3), pp. 611-642.

Guarino, N., and Welty, C. 2002. "Evaluating Ontological Decisions with OntoClean," *Communications of the ACM* (45:2), pp. 61-65.

Heflin, J. 2001. *Towards the Semantic Web: Knowledge Representation in a Dynamic, Distributed Environment*, Unpublished Doctoral Dissertation, University of Maryland, College Park.

Horridge, M., Rector A., Knublauch, H., Stevens, R., and Wroe, C. 2004. "A Practical Guide To Building OWL Ontologies Using the Protégé-OWL Plugin and CO-ODE Tool Edition 1.0," Volume 27, Manchester, UK: University of Manchester.

Jarvenpaa, S., and Machesky, J. 1989. "Data Analysis and Learning: An Experimental Study of Data Modeling Tools," *International Journal of Man–Machine Studies* (31), pp.367-391.

Khatri, V., Vessey, I., Ramesh, V., Clay, P., and Park, S. 2006. "Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge," *Information Systems Research* (17:1), pp. 81-99.

Ko, D.-G., and Dennis, A. R. 2011. "Profiting from Knowledge Management: The Impact of Time and Experience," *Information Systems Research* (22:1), pp. 134-152.

Linden, A. 2005. "Semantic Web Drives Data Management, Automation and Knowledge Discovery," Gartner Group, Stamford, CT (www.gartner.com).

Luck, M., and Inverno, M. 2001. "A Conceptual Framework for Agent Definition and Development," *The Computer Journal* (44:1), pp. 1-20.

Mayer, R. E. 2001. *Multimedia Learning*, New York: Cambridge University Press.

Mayer, R. E., and Moreno, R. 2003. "Nine Ways to Reduce Cognitive Load in Multimedia Learning," *Educational Psychologist* (38), pp. 43-52.

McGuinness, D. L., Smith, K. M., and Welty, C. 2004. *OWL Web Ontology Language Guide* (online at http://www.w3.org/TR/owl-guide/; retrieved February 14, 2007).

Motik, B. 2002. *Document on KAON Supported Modeling Primitives and Design Rationales* (online at http://km.aifb.uni-karlsruhe.de/kaon2/Members/motik/KAON-Supported Primitives_DesignDecisions.pdf; retrieved September 12, 2004).

Musen, M. 2004. "Knowledge Representation with Ontologies: The Present and Future," *IEEE Intelligent Systems* (19:1), pp.72-80.

Newell, A. 1982. "The Knowledge Level," *Artificial Intelligence* (18), pp. 87-127.

Parsons, J., and Cole, L. 2005. "What Do the Pictures Mean? Guidelines for Experimental Evaluation of Representation Fidelity in Diagrammatical Conceptual Modeling Techniques," *Data and Knowledge Engineering* (55:3), pp. 327-342

Pretz, J. E., Naples, A. J., and Sternberg, R. J. 2003. *Recognizing, Defining and Representing Problems*, Cambridge, UK: Cambridge University Press.

Protégé. 2003. *Protégé User Guide* (online at http://protege.stanford.edu/doc/users_guide/index.html; retrieved August 12, 2007).

Ram, S. 1995. "Intelligent Database Design Using the Unifying Semantic Model," *Information & Management* (29), pp. 191-206.

Rao, L., and Osei-Bryson, K. 2006. "Towards Defining Dimensions of Knowledge Systems Quality," *Expert Systems with Applications* (33:2), pp. 368-378.

Rumbaugh, J., Jacobson, I., and Booch, G. 1999. *The Unified Modeling Language Reference Manual*, Reading, MA: Addison Wesley.

Shaft, T. M., and Vessey, I. 2006. "The Role of Cognitive Fit in the Relationship Between Software Comprehension and Modification," *MIS Quarterly* (30:1), pp. 29-55.

Sowa, J. F. 2000. *Knowledge Representation: Logical, Philosophical, and Computational Foundations*, Pacific Grove, CA: Brooks Cole Publishing Co.

Spender, J. 2003. *Knowledge Fields: Some Post 9/11 Thoughts about the Knowledge Based Firm*, Berlin: Springer-Verlag.

Turetken, O., and Sharda, R. 2007. "Visualization of Web Spaces: State of the Art and Future Directions," *The DATABASE for Advances in Information Systems* (38:3), pp. 51-81.

Vessey, I., and Conger, S. A. 1994. "Requirements Specification: Learning Object, Process, and Data Methodologies," *Communications of the ACM* (37:5), pp. 102-113.

Wand, Y., Storey, V. C., and Weber, R. 1999. "An Ontological Analysis of the Relationship Construct in Conceptual Modeling," *ACM Transactions on Database Systems* (24:4), pp. 494-528.

Weber, R. 2003. "Conceptual Modeling and Ontology: Possibilities and Pitfalls," *Journal of Database Management* (14:3), pp. 1-20.

Wilson, T. D., and Dunn, E. W. 2004. "Self-Knowledge: Its Limits, Value, and Potential for Improvement," *Annual Review of Psychology* (55), pp. 493-518.

Zhang, J. 1991. "The Interaction of Internal and External Representations in a Problem Solving Task," in *Proceedings of the 13th Annual Conference of the Cognitive Science Society*, Hillsdale, NJ: Erlbaum, pp. 88-91.

Zou, Y. 2004. *Agent Based Services*. Unpublished Doctoral Dissertation, University of Maryland, Baltimore County.

About the Authors

Palash Bera is an assistant professor at the A.R. Sanchez Jr. School of Business at Texas A&M International University. He has a Ph.D. and a Master's degree in management information systems from the University of British Columbia. His research interests include conceptual modeling and the conceptual foundations of knowledge management. He has published in *Journal of Database Management* and *Communications of the AIS*. Palash has worked in executive and consulting positions in two multinational companies.

Andrew Burton-Jones is an associate professor at the Sauder School of Business at the University of British Columbia. He holds a B.Comm. and M. Inf. Sys. from the University of Queensland and a Ph.D. from Georgia State University. His first research stream seeks a deeper understanding of the meaning and consequences of system usage. His second stream aims to improve methods for representing the world in systems analysis and design. He has published in journals such as *Journal of the Association for Information Systems*, *Information Systems Research,* and *MIS Quarterly*. Previously, he was a senior consultant in a Big-4 consulting firm.

Yair Wand is CANFOR Professor of MIS at the Sauder School of Business at the University of British Columbia, Canada. He received his D.Sc. in Operations Research from the Technion (Israel Institute of Technology) and his M.Sc. in physics from the Weizmann Institute (Israel). His research interests include theoretical foundations and methods for information systems analysis and design. In particular, he has done work on the application of ontology to conceptual modeling.

MIS Quarterly

RESEARCH ARTICLE

GUIDELINES FOR DESIGNING VISUAL ONTOLOGIES TO SUPPORT KNOWLEDGE IDENTIFICATION

Palash Bera
A. R. Sanchez, Jr. School of Business, Texas A&M International University,
Laredo, TX 78041 U.S.A. {Palash.Bera@tamiu.edu}

Andrew Burton-Jones and Yair Wand
Sauder School of Business, The University of British Columbia,
Vancouver, BC V6T 1Z2 CANADA {Andrew.Burton-Jones@sauder.ubc.au} {Yair.Wand@sauder.ubc.ca}

Appendix A

A Brief Description of OWL

This OWL overview is based on the official OWL documentation from the World Wide Web Consortium (W3C) (McGuinness et al. 2004) and a guide to build OWL ontologies (Horridge et al. 2004).

OWL is the most recently developed ontology language from the W3C. OWL is based on RDF (resource description framework), which is accepted as a formal language of meta-data describing any web resources. The key constructs of OWL are *classes*, *individuals,* and *properties*. Classes in OWL are intended to represent concepts in a domain. OWL classes are associated with a set of individuals (or instances) that represent objects in the domain. OWL properties are used to assert general facts about classes and specific facts about individuals. These three concepts are further described below.

Classes

Classes provide a mechanism for grouping resources with similar characteristics. A class in OWL can be defined by declaring it a name. For example, by writing the following OWL syntax— <owl:Class rdf:ID="Customer">—a class named Customer is defined. OWL classes should correspond to a naturally occurring set of things in a domain. A class named owl:Thing is predefined, which means every class that is defined in the ontology is a subclass of owl:Thing. OWL classes are further defined through class descriptions. A class description describes an OWL class by specifying the conditions that an individual must satisfy to be a member of the class.

Individual

OWL individuals can be referred to as being instances of classes. It is intended that individuals should correspond to actual entities that can be grouped into these classes. For example, we can define a class, Customer, with instances of this class (OWL individuals) representing some specific customers. An individual can be minimally introduced by being declared a member of a class (either of the predefined top class owl:Thing or some other class defined in an ontology). For example,

```
<owl:Thing rdf:ID="SomeBody">
<owl:Human rdf:ID="John_Doe">
```

In the above syntax, the first statement introduces an individual SomeBody simply as an instance of owl:Thing (no further information about this individual has been provided yet). The second statement declares another individual John_Doe, as an instance of the class Human.

Properties

Properties in OWL are binary relationships. A property links *a subject* (an OWL individual) to *an object* (an OWL individual or a data value), and the object is considered to be a value of this property for the subject. These subjects and objects in OWL are termed *domain* and *range* respectively. Properties link individuals from the domain to individuals from the range.

Properties in OWL are mainly two types: *datatype* and *object*. Datatype properties link individuals to data values. For example, we may define a datatype property "hasAge" to represent the age of a person, that is, to link an individual (such as John) to a non-negative integer representing age (such as 25). Instances of object properties relate individuals to individuals. For example, in an ontology that describes persons, we can define an object property "hasMother" to relate individuals representing persons (as a class) to other individuals representing mothers (as a class). The syntax of this situation is shown below, and an equivalent diagram for the syntax is shown adjacent to it. It is a standard practice to show the object property in the diagram, both on the arrow and inside the class (from where the property originates).

```
<owl:Class rdf:ID="Person"/>
  <owl:Class rdf:ID="Mother"/>
  <owl:ObjectProperty rdf:ID="hasMother">
    <rdfs:domain rdf:resource="#Mother"/>
    <rdfs:range rdf:resource="#Person"/>
</owl:ObjectProperty>
```

References

Horridge, M., Rector A., Knublauch, H., Stevens, R., and Wroe, C. 2004. "A Practical Guide To Building OWL Ontologies Using the Protégé-OWL Plugin and CO-ODE Tool Edition 1.0," Volume 27, Manchester, UK: University of Manchester.

McGuinness, D. L., Smith, K. M., and Welty, C. 2004. *OWL Web Ontology Language Guide* (online at http://www.w3.org/ TR/owl-guide/; retrieved February 14, 2007).

Appendix B

Specific Rules to Model Interactions in OWL

The following rules are offered to provide additional assistance to help modelers implement the guidelines proposed in this paper. They are at a fairly low level of detail to provide specific direction to modelers working with OWL.

1. Instances of interacting classes must have at least *one* mutual property, which is modeled as the property of the interaction classes. In the absence of any mutual property, instances do not interact.

2. Each interaction class must have at least *two* object properties (that can be identified with appropriate prefixes such as "involves") linking it to the interacting class. This restriction reflects that at least two interacting classes are necessary to form one interaction class.

3. Each interacting class must have at least *one* instance. By enforcing this restriction, it is made explicit that instances that may interact with each other exist.

4. Each interaction class represents a set of related concurrent mutual properties (arising from the same interaction). Different interaction classes should be used if sets of properties are not concurrent.

Appendix C

Ontologies Used in Experiments 1 and 2

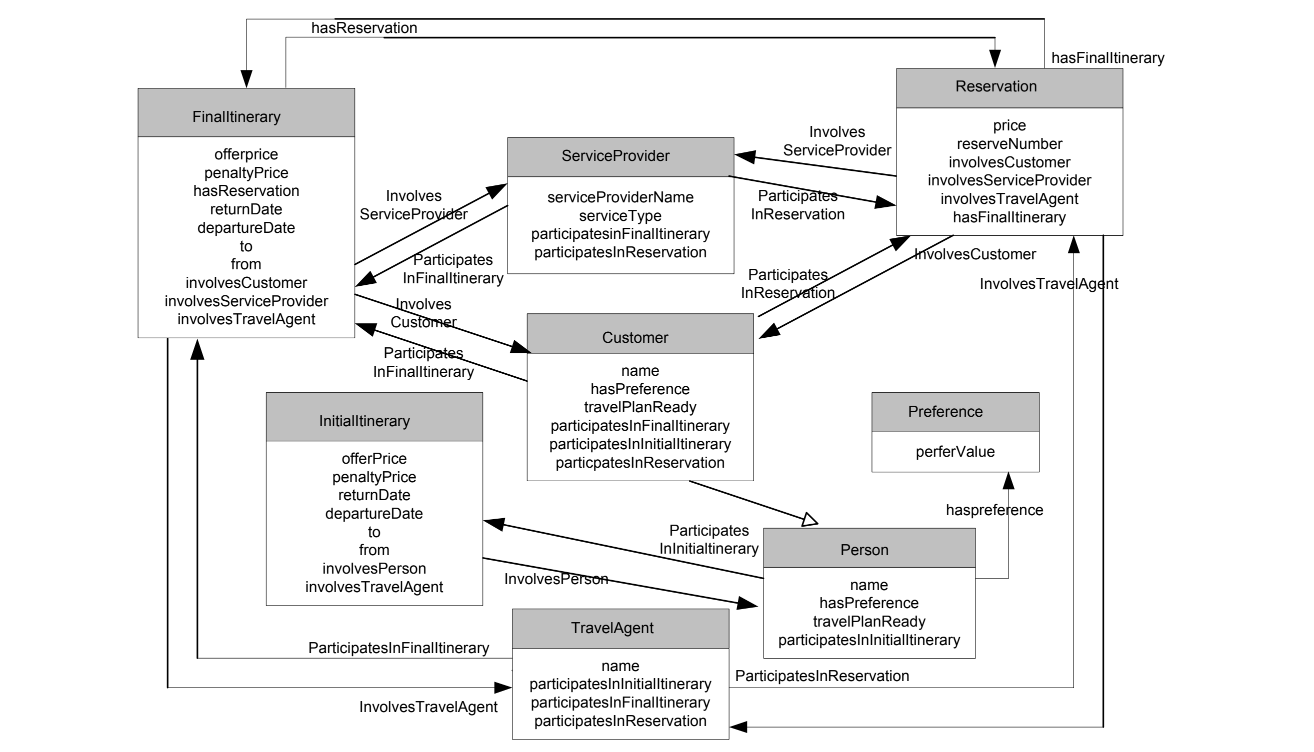
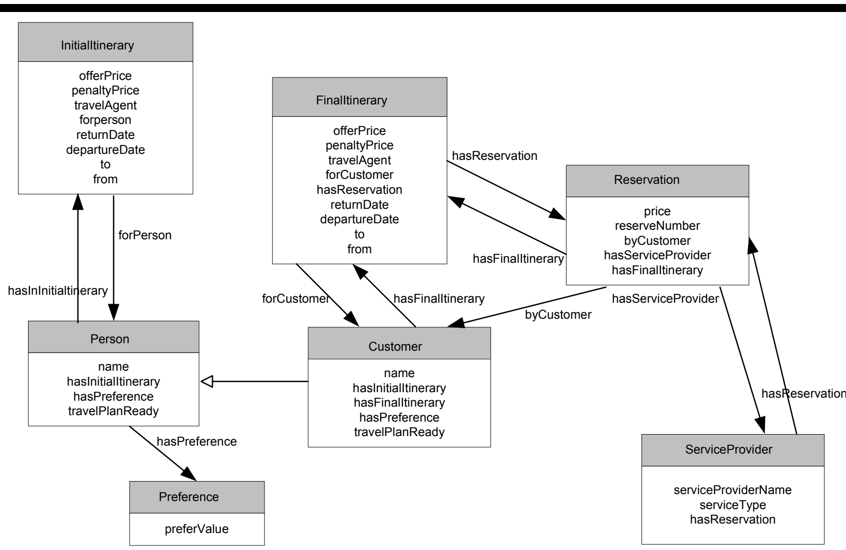


Figure C1. Experiment 1: Guided Travel Ontology



Explanation of the Violations

This version of the unguided ontology violates all of the guidelines related to classes and their connections. Guideline 1 is violated because one of the relevant interacting classes ("TravelAgent") is omitted and shown merely as a property of the "InitialItinerary" and "FinalIntinerary" classes. Guidelines 3 and 4 are violated as the interaction and the interacting classes are not connected using prefixes involves and participates in. Moreover, the "Reservation" class is not connected to the "TravelAgent" class as the "TravelAgent" class is not shown.

Figure C2. Experiment 1: Unguided Travel Ontology

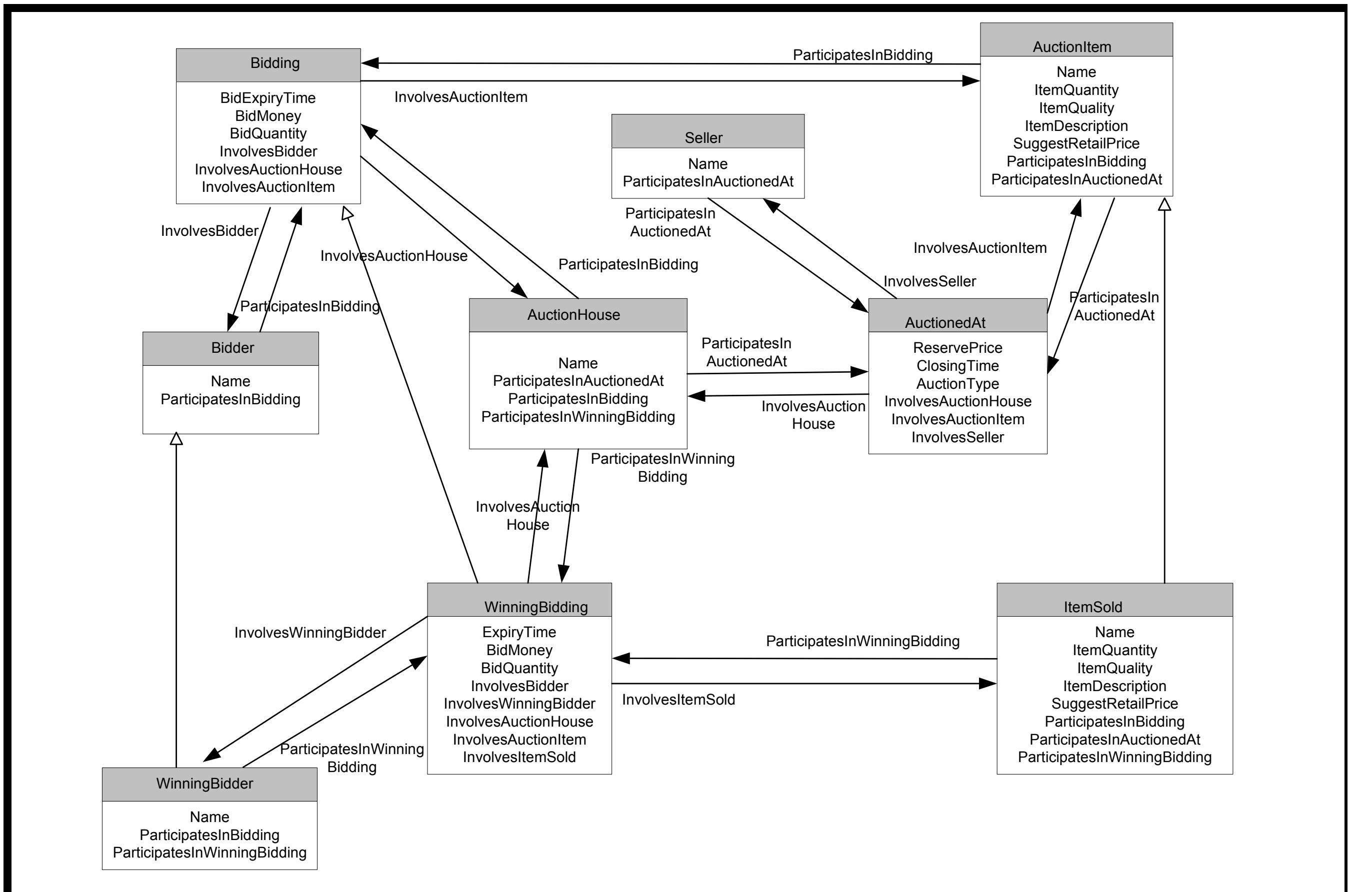
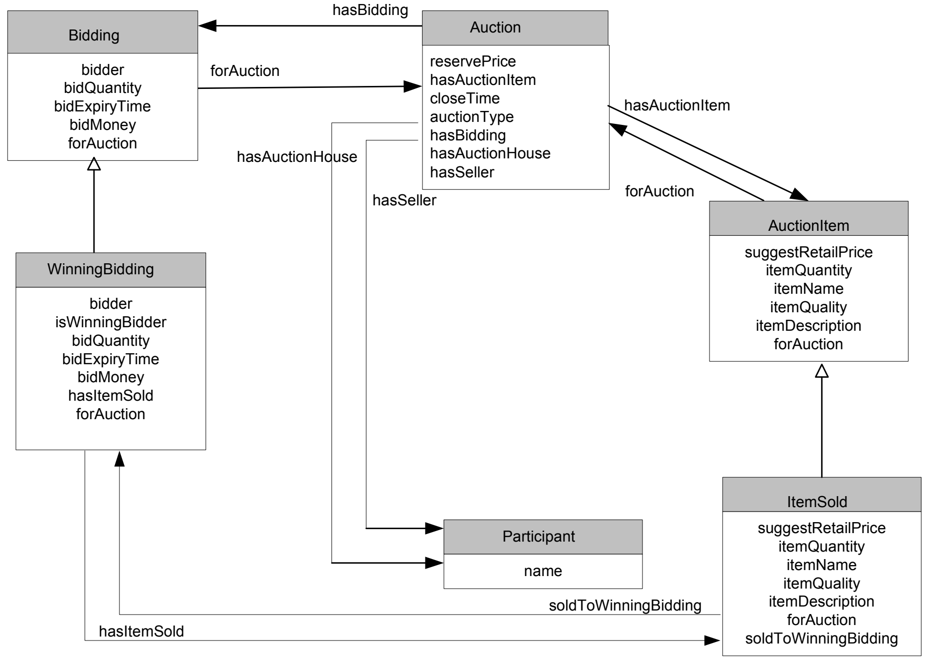


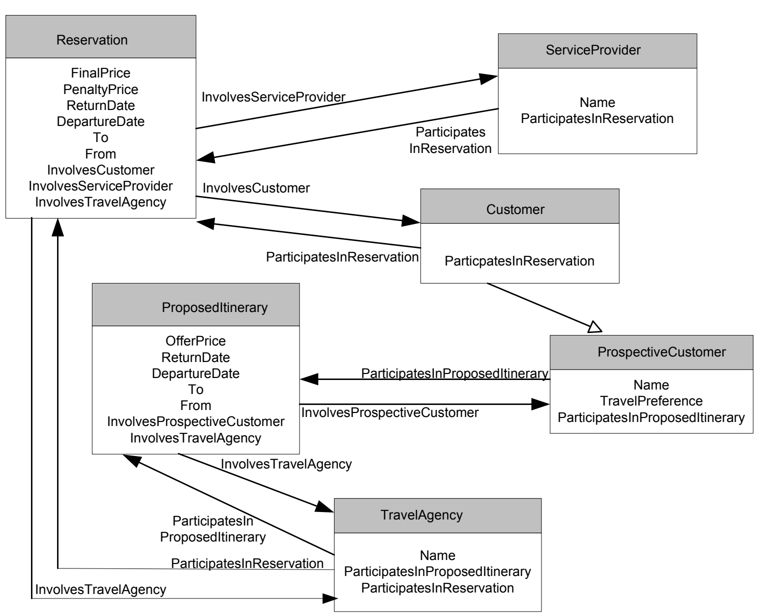
Figure C3. Experiment 1: Guided Auction Ontology



Explanation of the Violations

This version of the unguided ontology violates all of the guidelines. Guideline 1 is violated because several interacting classes are not shown; they are shown instead as properties of interaction classes. For example, "AuctionHouse" and "Seller" are modeled as properties of "Auction." Guideline 2 is violated as the interaction classes contain properties (such as "bidder" in "Bidding") that do not represent mutual properties. These properties are represented more clearly in the guided version (for example, by showing "involvesBidder" in the "Bidding" class, which makes the interaction explicit). Guidelines 3 and 4 are violated as the interaction and interacting classes are not connected using prefixes involves and participatesIn. Moreover, some connections are not shown at all, such as between "Bidding" and "Bidder" because the "Bidder" class is not shown.

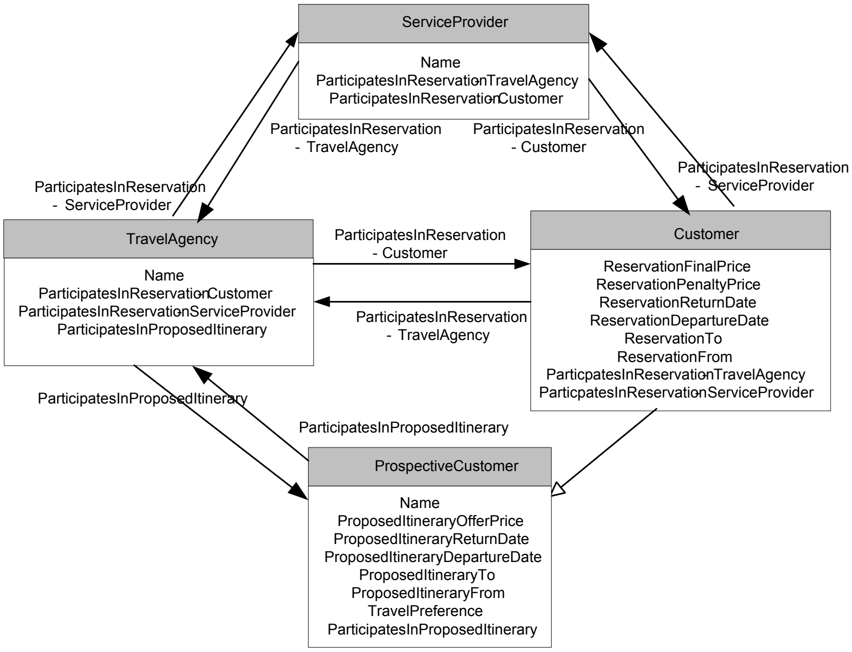
Figure C4. Experiment 1: Unguided Auction Ontology



Narrative for the Guided Ontology:

A travel agency helps prospective customers to organize trips. A prospective customer has travel preferences and informs the travel agency about them. The travel agency proposes several itineraries, the prospective customer reviews them and chooses the final one. A travel itinerary contains information about the destination, offered ticket price, departure and return dates and price. At a given time the travel agency deals with only one trip for a prospective customer. A reservation is a contract between the customer and the service provider arranged by the travel agency. Once an itinerary is agreed to, the reservation is made by the travel agency in consultation with the service providers (airlines, railways, etc.). A reservation also includes a penalty in case a customer cancels the reservation after a given date.

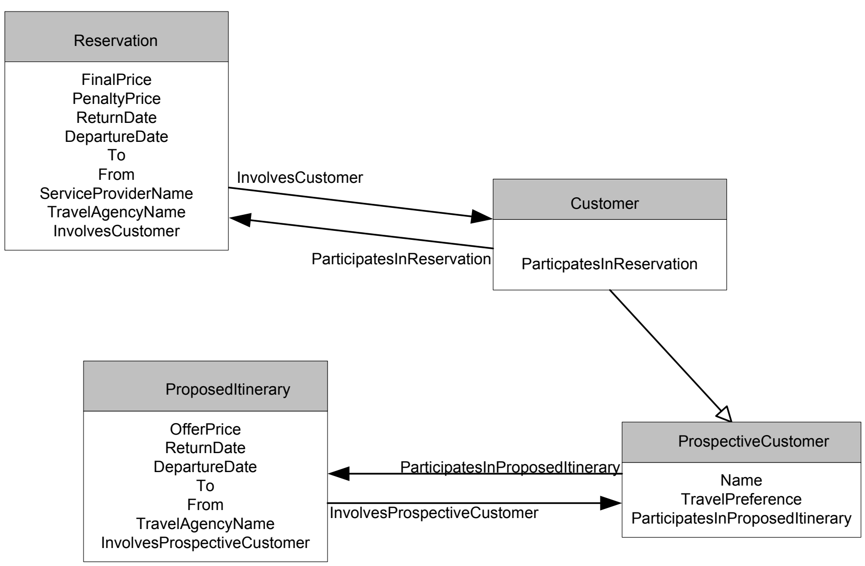
Figure C5. Experiment 2: Guided Travel Ontology and Associated Narrative



Explanation of the Violations

This version violates all four guidelines. Guideline 1 is violated by removing the interaction classes and modeling them as properties of interacting classes. For example, the class "Reservation" does not exist anymore in the diagram, rather the properties of the "Reservation" class (such as FinalPrice, PenaltyPrice) are modeled as properties of the Customer class. Guideline 2 is violated as the mutual properties of entities in the interacting classes are no longer in the interaction classes (such as ReservationFinalPrice). Because guidelines 1 and 2 are violated, guidelines 3 and 4 are violated as well (i.e., some of the links between interacting and interaction classes disappear).

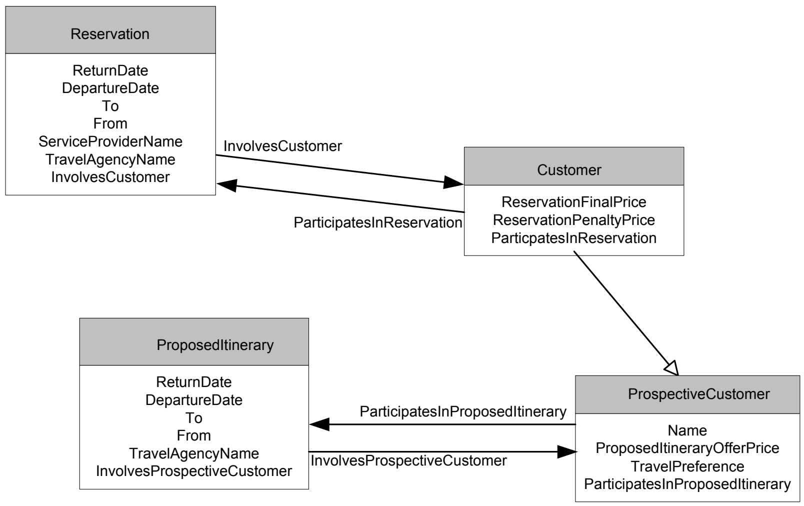
Figure C6. Experiment 2: Unguided Travel Ontology (Type 1)



Explanation of the Violations

This diagram violates guidelines 1, 3, and 4. Guideline 1 is violated as most of the interacting classes (such as "TravelAgency" and "ServiceProvider") are removed and modeled as properties of interaction classes (such as in "Reservation"). As guideline 1 is violated, guidelines 3 and 4 are violated as well.

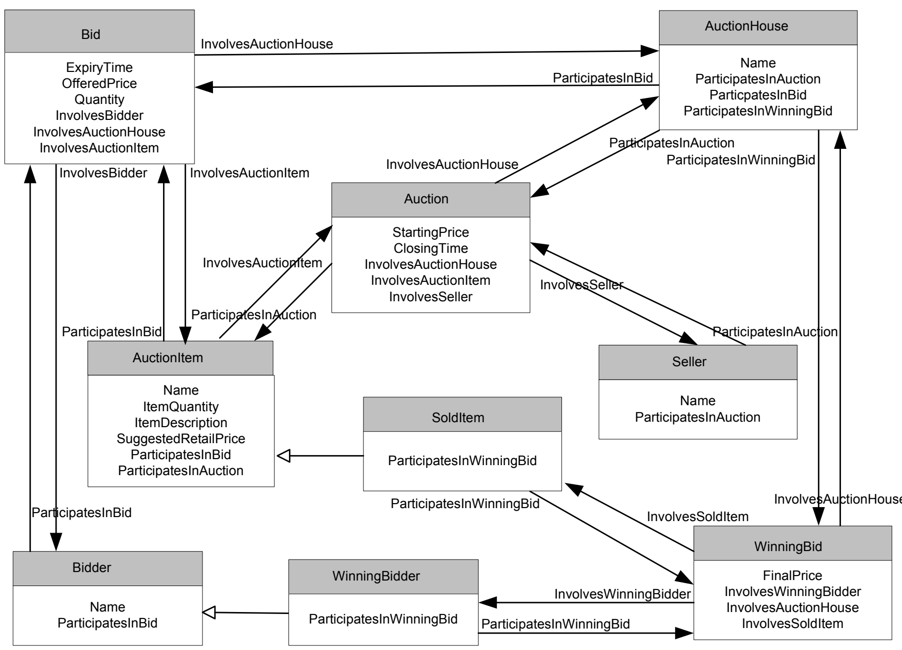
Figure C7. Experiment 2: Unguided Travel Ontology (Type 2)



Explanation of the Violations

In this version, all of the guidelines are violated. Guideline 1 is violated as most of the interacting classes (such as "TravelAgency" and "ServiceProvider") are removed and modeled as properties of interaction classes (such as in the "Reservation" class). Guideline 2 is violated as some properties of the interaction classes (such as FinalPrice and PenaltyPrice of "Reservation") are removed and placed as the properties of interacting classes (such as in the "Customer" class). Thus, guideline 2 is also violated. As guidelines 1 and 2 are violated, guidelines 3 and 4 are violated as well.

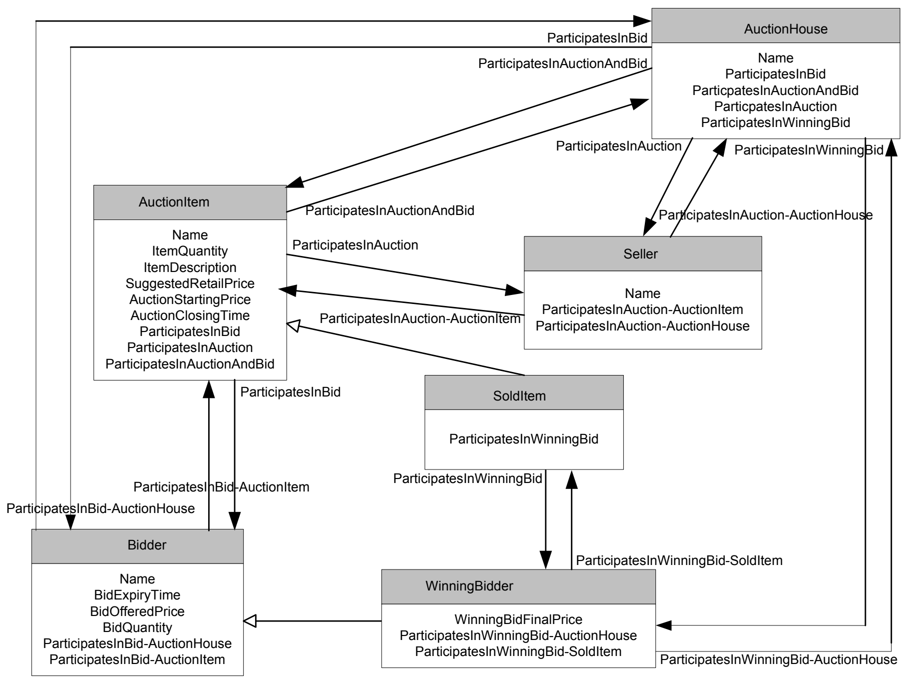
Figure C8. Experiment 2: Unguided Travel Ontology (Type 3)



Narrative for the Guided Auction Ontology:

In an auction there are three participants: a seller, an auction house, and a bidder. The bidder wishes to obtain the highest price possible. The auction house represents the seller and announces the current bids. The goods sold in the auction are termed the Auction Items. An auction item may comprise multiple goods, for example, a travel package may include two airline tickets and one hotel room. Two important aspects of an auction are the closing time and starting price. A suggested retail price may also be indicated in an auction item. A bidder submits a bid to the auction house indicating a price and an expiration time. Typically there may be several bidders for an auction item. The highest bidder becomes the winning bidder and pays the final price, which is equal to that of the winning bid.

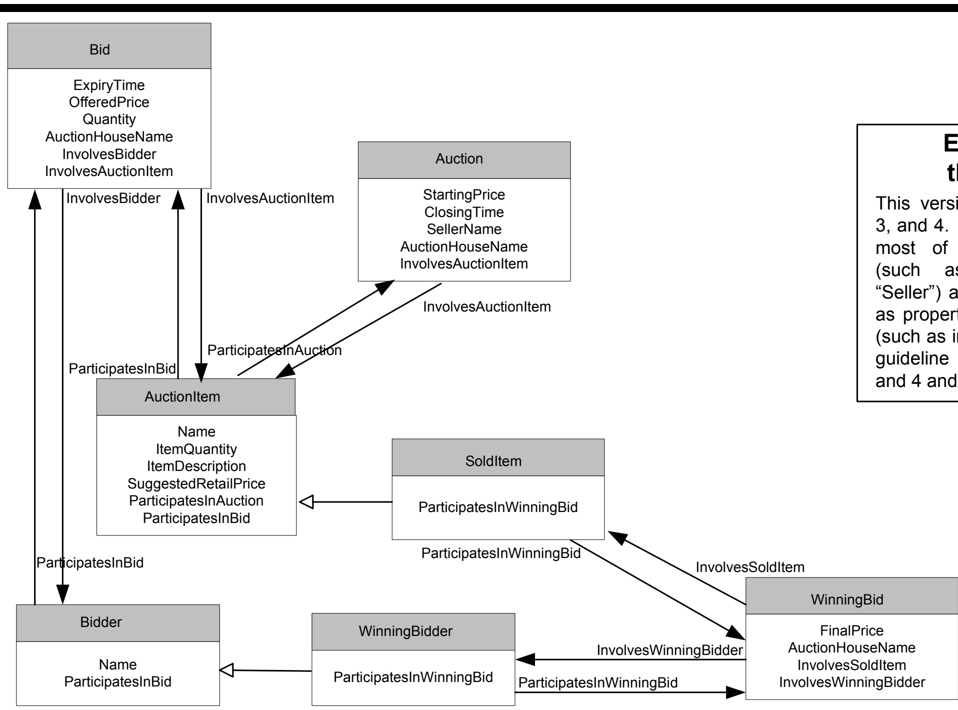
Figure C9. Experiment 2: Guided Auction Ontology and Associated Narrative



Explanation of the Violations

This version violates all four guidelines. Guideline 1 is violated by removing the interaction classes and modeling them as properties of interacting classes. For example, the class "Auction" does not exist anymore in the diagram, rather the properties of the "Auction" class (such as ClosingTime, StartingPrice) are modeled as the properties of the "AuctionItem" class. Guideline 2 is also violated as the mutual properties of entities in the interacting classes are no longer in the interaction classes (such as BidExpiryTime). Because guidelines 1 and 2 are violated, guidelines 3 and 4 are violated as well.

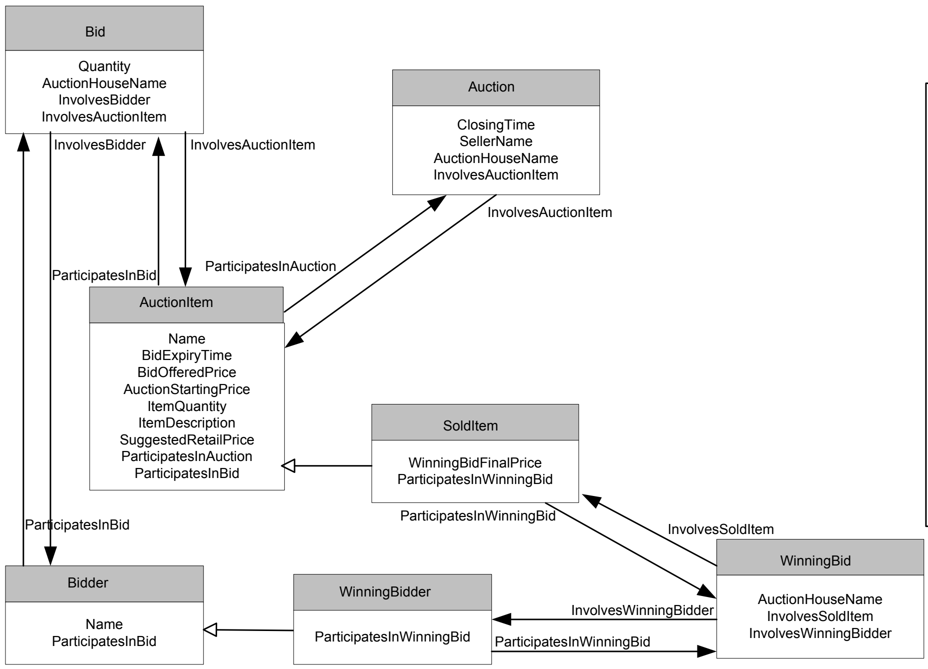
Figure C10. Experiment 2: Unguided Auction Ontology (Type 1)



Explanation of the Violations

This version violates guidelines 1, 3, and 4. Guideline 1 is violated as most of the interacting classes (such as "AuctionHouse" and "Seller") are removed and modeled as properties of interaction classes (such as in the "Auction" class). As guideline 1 is violated, guidelines 3 and 4 are violated as well.

Figure C11. Experiment 2: Unguided Auction Ontology (Type 2)



Explanation of the Violations

In this version, all of the guidelines are violated. Guideline 1 is violated as most of the interacting classes (such as "AuctionHouse" and "Seller") are removed and modeled as properties of interaction classes (such as the "Auction" class). In addition, some of the properties of the interaction classes (such as StartingPrice of "Auction") are removed and shown as the properties of interacting classes (such as in "AuctionItem"). Thus guideline 2 is also violated. As guidelines 1 and 2 are violated, guidelines 3 and 4 are violated as well.

Figure C12. Experiment 2: Unguided Auction Ontology (Type 3)

Appendix D

Test Materials

The questions below were the same in Experiments 1 and 2.

Comprehension Questions: Travel Domain [Answers are true/false]

1. Every final itinerary must have a reservation
2. A service provider is involved in preparing initial itineraries
3. Every person is able to make reservations
4. Preparing final itinerary involves service providers
5. A reservation can be performed without involving a travel agent
6. A travel agent is involved in preparing final itineraries
7. Every initial itinerary must have a reservation
8. Reservation can be made without service provider's involvement
9. Every itinerary should include departure date and return date

Knowledge Identification Tasks: Travel Domain

1. You are asked to develop a procedure (a set of rules) for cancellation of a customer's reservation. Using the above diagram as guidance, please specify the **questions** you will ask in order to develop a procedure for canceling a customer's reservation. Provide as many responses as you can.

2. You are asked to develop a procedure (a set of rules) for allowing customers to travel without having reservations. Using the above diagram as guidance, please specify the **questions** you will ask in order to develop a procedure for allowing customers to travel without having reservations. Provide as many responses as you can.

3. You are asked to develop a procedure (a set of rules) for allowing customers to change their reservations. Using the above diagram as guidance, please specify the **questions** you will ask in order to develop a procedure for allowing customers to change their reservations. Provide as many responses as you can.

Knowledge Identification Tasks: Auction Domain

1. You are asked to develop a procedure (a set of rules) to allow canceling bids proposed by bidders. Using the above diagram as guidance, please specify the **questions** you will ask in order to develop a procedure to allow retracting bids proposed by bidders. Provide as many responses as you can.

2. You are asked to develop a procedure (a set of rules) for stopping bidders to buy directly from sellers without the knowledge of auction house. Using the above diagram as guidance, please specify the **questions** you will ask in order to develop a procedure to stop bidders buying directly from sellers without the knowledge of auction house. Provide as many responses as you can.

3. You are asked to develop a procedure (a set of rules) for preventing winning bidders not paying for the item that they have won. Using the above diagram as guidance, please specify the **questions** you will ask in order to develop a procedure for preventing winning bidders not paying for the item that they have won. Provide as many responses as you can.

Sample Answers for Knowledge Identification Tasks (Travel Domain) Used as Feedback

Response for Task 1
How to check the record of the customer who wants to cancel.
How to inform the customer about the penalty for cancellation.
How to pay the penalty price (if there is a penalty for cancellation).
How late will a customer be able to cancel a reservation?
How to contact the service provider/travel agent to cancel a reservation.
How would the travel agent inform the service provider about a cancellation?
How to refund the money to the customer from the travel agent.

Response for Task 2
How to inform the customers that all seats are reserved or not reserved.
Can a final itinerary printout be used as a substitute of a reserved ticket?
How do service providers deal with double booking?
How is the price assigned for customers who travel without reservations?
How does the customer pay when he/she travels without reservations?
How to provide (assure) customers' preference are available.
How to involve (inform) a service provider in preparing a final itinerary.

Response for Task 3
How to inform the service provider/travel agent about the change.
How late will a customer be able to change a reservation?
How to check the original reservation, itinerary and customer information.
How to inform the customer that the reservation has been changed (or not changed).
Is there a penalty to change reservation? If so, how can it be applied?
How to pay the penalty price (if there is a penalty) or additional amount for the change.
Whether to delete the current reservation before making the changes.
How should the final itinerary be changed according to the change in reservation?
Whether to issue another reservation number or keep the old reservation number.

Items for Prior Modeling Knowledge (Seven-Point Likert Scale)

1. To what extent do you know data modeling concepts (such as entities, classes, and properties)?
2. To what extent do you have experience in using data modeling concepts (such as entities, classes, and properties)?

Items for Prior Domain Knowledge (Seven-Point Likert Scale)

1. Over the last two years, to what extent have you made travel reservations?
2. Over the last two years, to what extent have you participated in auctions (including online auctions)?
3. To what extent do you have knowledge of reservation procedures (e. g. , used by ticketing companies, airlines)?
4. To what extent do you have knowledge of auction procedures?

Items for Perceived Ease-of-Understanding (Seven-Point Likert Scale)

1. To what extent is the information represented in the diagrams easy to understand?
2. To what extent is the information represented in the diagrams confusing?
3. Trying to understand all of the information represented in the diagram required a lot of mental effort.
4. Overall I found the information represented in the diagrams easy to interpret.

Items for Perceived Understanding (Seven-Point Likert Scale)

1. To what extent did you understand all of the information represented in the diagram?
2. To what extent did you comprehend all of the information represented in the diagram?
3. Overall I grasped all the information represented in the diagram.

Copyright of MIS Quarterly is the property of MIS Quarterly & The Society for Information Management and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.