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DEALING WITH COMPLEXITY IN INFORMATION SYSTEMS MODELING: DEVELOPMENT AND EMPIRICAL VALIDATION OF A METHOD FOR REPRESENTING LARGE DATA MODELS

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Abstract

One of the most serious practical and theoretical limitations of the entity-relationship (E-R) model is its inability to cope with complexity. Once E-R models exceed a certain threshold of size, they become difficult to understand, document and maintain. This paper describes the development and empirical validation of a method for representing large E-R models called leveled data modeling (LDM). A combination of research methods were used to validate the method. Action research was first used to test and refine the method in a real-world setting. Eight action research studies were conducted in eight different organizations. Once the method had become stable, two laboratory experiments were conducted to evaluate its effectiveness compared to the standard E-R model and methods previously proposed in the literature. Finally, a field experiment was conducted using experienced practitioners to evaluate the likelihood of the method being accepted in practice. The resulting method defines a general approach for managing complexity which could be applied to any information systems modeling technique. The research findings thus have general implications for developing more effective IS design techniques. Another contribution of the paper is that it illustrates a systematic, multi-method approach to empirically validating an IS design method.

Keywords: Entity-relationship (E-R) model, conceptual model, requirements analysis, complexity, action research, experimental research

Introduction

The Problem of Complexity in Data Modeling

The entity-relationship (E-R) Model is probably the most successful information systems analysis technique ever developed. Since its original formulation in the 1970s (Chen 1976), it has become the international standard for data modeling and has been used to design database schemas for over two decades (Thalheim 1999). A recent survey of practice showed that E-R modeling was not only the most frequently used data modeling technique, but also the most frequently used IS analysis technique generally (Davies et al. 2003). One of the most serious practical and theoretical limitations of the E-R model is its inability to cope with complexity (Akoka and Comyn-Wattiau 1996; Allworth 1996, 1999; Feldman and Miller 1986; Gandhi et al. 1994; Gilberg 1986; Simson 1989; Teory et al. 1989; Wand and Weber 1993; Weber 1997). Neither the standard E-R model nor the extended entity-relationship (EER) model provide explicit abstraction mechanisms for managing complexity (Weber 1997). A number of methods

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have been proposed in the literature to address this issue, but so far none of these have been widely accepted in practice. Consequently, it remains an open research issue (Thalheim 1999).

Practical Problems with Large Data Models

The major practical problems with large data models are

- End user understanding: When data models exceed a certain size, they become difficult for people, especially end users, to understand. Due to limits on short-term memory, humans have a strictly limited capacity for processing information. This is estimated to be “seven, plus or minus two” concepts at a time (Miller 1956; see also Baddeley 1994; Newell and Simon 1972). If the volume of information exceeds these limits, a state of information overload ensues and comprehension degrades rapidly (Lipowski 1975). Empirical studies show that application data models contain an average of 95 entities, while enterprise data models contain 536 entities (Maier 1996), exceeding human cognitive capacity many times over.
- Documentation and maintenance (analyst’s perspective): When data models exceed a certain size, they become difficult to document and maintain. Representing E-R models of real-world complexity as single diagrams results in crossed lines, unreadable text, and the need for ever-increasing sizes of paper (Feldman and Miller 1986; Simsion 1989).

Theoretical Problems with Large Data Models

Wand and Weber (1990, 1995) have proposed a theory of representation (referred to as the Bunge-Wand-Weber or BWW ontology) that defines a comprehensive set of ontological concepts needed to model the real world. This provides a theoretical basis for evaluating and comparing different modeling notations (e.g., Green and Rosemann 2000; Opdahl and Henderson-Sellers 2002). In evaluating the E-R model, Wand and Weber (1993) found that a major deficiency in the method was that it lacked constructs for representing systems, subsystems, decomposition, and level structures, which are the constructs needed to manage complexity. This means that the E-R model is *ontologically incomplete*. Wand and Weber argue that these constructs are critical to the design and implementation of information systems and our ability to understand real world phenomena.

Objectives of this Paper

This paper describes the development and empirical validation of a method for managing complexity of large E-R models. The objectives of this method were to address the practical problems identified with large data models

- to improve end user understanding (O_1)
- to simplify documentation and maintenance (O_2)

The problem of ontological incompleteness is addressed as a natural consequence of solving these problems, as the missing ontological constructs are precisely those needed to manage complexity.

Leveled Data Models

A Street Directory as a Referent Problem

The problem of representing large and complex models is one that is faced in many disciplines. Therefore, a natural starting point for this research was to look at how similar problems have been solved in other domains. This is an example of *analogical reasoning*; a problem solving approach in which a solution is found by adapting a solution from another (referent) domain (Gentner 1983; Holyoak 1985; Keane 1985, 1988). A city street directory (e.g., the London A-to-Z) is an example of a successful solution to the problem of representing a large and complex model. It provides a simple yet effective way of packaging a large amount of information in a way that people can easily understand. It has evolved over a long period of time, and has been proven to be highly effective in practice. Evidence of its maturity can be seen in its consistency over time, from one map maker to another, and across different countries. The common structural elements of a street directory are

- A *key map*, which provides an overview of the region covered by the directory and how it is divided into subsystems (detail maps).
- A set of numbered *detail maps*, each showing part of the region in full detail. These include *inter-map references*, which show how the maps relate to each other.
- A set of *indexes*, listing streets, towns, suburbs, and other places of interest, together with their map reference.

Leveled Data Model Architecture

Closely based on the street directory solution, a method was developed for representing large E-R models. This was called leveled data modeling (LDM), as it allows a large data model to be represented at multiple levels of abstraction. The components of an LDM are (cf. Figure 1):

- A *context data model* provides an overview of the model and how it is divided into subsystems (*subject areas*). This is represented as an E-R model with subject areas shown as entities and *boundary relationships* (relationships which cross subject area boundaries) shown as relationships between them. This corresponds to the key map in a street directory.
- A set of named *subject area data models*, each showing a manageable-sized subset of the data model in detail. These correspond to detail maps in a street directory. Subject area data models are shown as standard E-R models, with *foreign entities* to show relationships to entities on other subject areas. Foreign entities are shown as shaded entities with their primary subject area in brackets, and correspond to inter-map references in the street directory.
- A range of *indexes* are used to help locate individual objects (entities, relationships, and attributes) within each subject area.

This mirrors the structure of the street directory almost exactly. The model may be organized into any number of levels, depending on the size of the underlying data model, resulting in a hierarchy of models at different levels of detail. At each level, the diagrams use the standard conventions of the E-R model (with minor modifications).

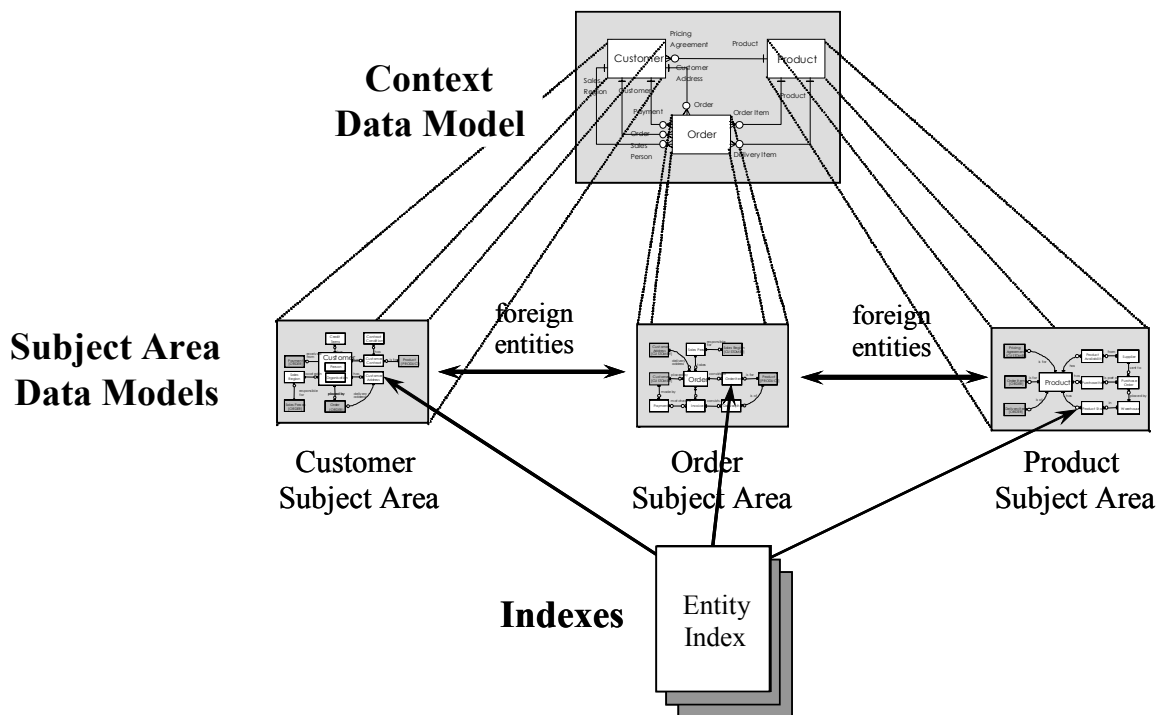


Figure 1. Leveled Data Model Architecture

Research Methodology

Validation of IS Design Methods

The question of how to validate IS design methods has been a longstanding issue in the IS field (e.g., Fitzgerald 1991; Ivori 1986; Olle et al. 1983; Olle et al. 1982, 1986; Weber 1997; Wynekoop and Russo 1997). There are inherent problems evaluating any methodology or design technique since there is typically no theory, no hypotheses, no experimental design, and no data analysis to which traditional evaluation criteria can be applied (Weber 1997). As a result, IS design research tends to emphasize the development of new design methods and frameworks, while addressing the use and evaluation of methods in practice in only a limited fashion (Bubenko 1986; Curtis 1986; Fitzgerald 1991; Moody and Shanks 2003; Westrup 1993; Wynekoop and Russo 1997). A possible reason for the lack of validation of IS design methods is the philosophical and methodological problems involved in validating *methods* as opposed to *theses*. According to Rescher (1977), human knowledge consists of two types:

- *Theses* or “knowledge that”: these define statements or assertions about the world.
- *Methods* or “knowledge how”: these define ways of doing things.

Knowledge that or propositional knowledge has been the primary focus of scientific research, which is generally about establishing the truth of particular propositions (*hypotheses*). Rescher argues that an entirely different approach is required to validate methodological knowledge. The reason is that methods have no truth value, only *pragmatic value*: a method does not describe any external reality, so it cannot be true or false, only effective or ineffective. Unlike theses, methods cannot be established deductively from known facts or inductively from observations. The validity of a method can only be established by applicative success in practice. The objective of validation should not be to demonstrate that the method is “correct” but that it is rational practice to adopt the method based on its *pragmatic success*. Pragmatic success is defined as the efficiency and effectiveness with which a method achieves its objectives.

Research Phases

There are a wide variety of research methods which may be used in conducting IS research (Baskerville and Wood-Harper 1996; Galliers 1991, 1992; Nunamaker et al. 1991; Shanks et al. 1993; Wynekoop and Russo 1997). Different research methods may be appropriate in different situations, depending on the research question and the state of knowledge in the area. In general, a combination of research methods may be most effective in achieving a particular research objective (Duchon 1988; Fitzgerald 1991; Galliers 1992; Jick 1979; Kaplan and Lee 1991; Neuman 2000; Wynekoop and Russo 1997). A combination of field and laboratory, quantitative and qualitative, research methods were used to evaluate the LDM method.

1. Field testing: Action research was used to test and refine the method in a range of real world environments. Multiple cycles and cases were used.
2. Laboratory experiment 1: A laboratory experiment was conducted to evaluate the effectiveness of the method in improving end-user understanding (O₁).
3. Laboratory experiment 2: A second laboratory experiment was conducted to evaluate the effectiveness of the method in simplifying documentation and maintenance (O₂).
4. Practitioner acceptance testing: A field experiment was conducted to evaluate the likelihood of the method being adopted in practice.

Field Testing

Action Research

A major barrier to the empirical validation of IS design methods is that it is very difficult to get new approaches accepted and used in practice. Practitioners who have developed familiarity and expertise with existing techniques are reluctant to adopt academic

approaches that are theoretically sound but unproven in practice (Avison et al. 1999; Bubenko 1986; Wynkoop and Russo 1997). *Action research* provides a method for testing and refining research ideas by applying them in practice (Baskerville and Wood-Harper 1996; Hatten et al. 1997; McCutcheon and Jurg 1990). One of its advantages is that it can help overcome the problem of persuading practitioners to adopt new techniques, and overcome the cultural divide that exists between IS academics and practitioners (Avison et al. 1999; Checkland 1991; Moody and Shanks 2003).

Research Questions Addressed

The two broad research questions addressed by the action research studies were

- Is the LDM method effective in achieving its objectives (O_1 and O_2)?
- How can it be improved? That is, how can the method be modified so that O_1 and O_2 are more efficiently or more effectively achieved?

Overview of the Action Research Program

A weakness of action research studies is that the results are often not generalizable beyond the organization and situation being studied. For this reason, it is important to conduct a range of studies in different environments (Dick 1999). As part of an ongoing action research program, the method was applied in eight different organizations. Half of the studies were conducted in the public sector and half in the private sector, and all were in different industries.

Action (Practical) Outcomes

One of the unique characteristics of action research is that it results in both *action (practical) outcomes* and *research (theoretical) outcomes*. Action outcomes are benefits for the organization as a result of the intervention, while research outcomes are refinements to the research idea. The practical benefits found as a result of using the method were

- Improved end user understanding: All end users involved in the studies felt that models represented in leveled form were easier to understand than those in standard E-R form (which they were using prior to introduction of the method).
- Reduced documentation effort: The majority of analysts reported that the method reduced the effort required to document models. However a significant minority did not, mainly because of the need to manually add and maintain links (foreign entities) between diagrams. This could be addressed by direct CASE tool support for the method.
- Simplified maintenance: The method simplified evolution of models by dividing them into separate modules, which could be independently developed and maintained by different analysts or project teams.
- Improved verification: Subject areas were found to be a convenient unit for verifying data models with end users, which resulted in more comprehensive verification of models, and a wider pool of users being involved. This was also perceived to be much more cost-effective in terms of users' time.
- Management of analysis work: This was an unexpected benefit of the method, as it was not one of the original objectives of the method. However, subject areas proved to be a useful tool for managing the analysis task in large application development projects: different analysts and/or project teams could be assigned to work on different subject areas, with interdependencies between them clearly defined by foreign entities.
- Database design: Database designers were not originally considered as stakeholders in the design of the method, and the method in its original form did not adequately meet their needs. A range of modifications were made to facilitate translation to database design.

In each study, the method was initially applied on a single project, but in seven out of eight cases, it was subsequently adopted as a corporate-wide standard. In these cases, change of practice was not confined to the project in which it was applied, but to

the organization as a whole. This provides strong evidence that it was perceived by stakeholders to be a genuine improvement on previous practices (i.e., the standard E-R model).

While this may seem to present a rather rosy picture of the method's success in practice, many iterations (action research cycles) were required to get it to this level. A major advantage of action research is that it allows a method to evolve as part of an iterative learning process, so is ideally suited for use in the early, developmental stages of a method. Any new method is unlikely to be successful the first time it is applied in practice so traditional hypothesis-testing approaches are likely to be premature.

Research (Theoretical) Outcomes

The method evolved significantly as a result of the action research program. All of the original components of the method were modified and four new components were added. The most significant changes to the method were

- Context data model: The representation of the context data model changed drastically as a result of the action research program. The original E-R-like representation was replaced by a pictorial representation, with subject areas shown as graphical images and boundary relationships using arrows. The representation was further simplified by only showing the most important boundary relationships rather than all relationships.
- Foreign entities: Both single and bidirectional foreign entity links were experimented with, but bidirectional links (where each boundary relationship is duplicated on both subject areas together with the entities involved) were found to provide the optimal level of redundancy. The convention used for foreign entities was changed from shaded boxes to dotted boxes to emphasize that they were part of the background.
- Subject area matrix: This was an *ad hoc* extension to the method, which was introduced when the original representation of the context data model proved to be unworkable. However it proved a useful tool for project management purposes and was retained as a permanent component of the method.
- External entities: These were introduced to show references to entities in external projects or systems.
- Decomposition procedure: In the original method, the process of grouping entities into subject areas was left largely to the analyst's judgement. The decomposition rules were refined to increase consistency between different analysts using the method, to the point that they were used as the basis for automatic clustering (Moody and Flitman 1999).
- Indexes: Only the entity index was retained from the original set of indexes.
- Data Decomposition Diagram: This provides an overview of the structure of the model in the form of a hierarchy chart, but is only useful when three or more levels of decomposition are used.

Stabilization of the Method

Most of the changes to the method occurred in the first two action research studies. After this, the number of changes steadily reduced, and the last three studies resulted in virtually no change at all. This provided strong evidence that the method was now stable. In the evolution of any method, eventually one reaches a point of stabilization after which all versions of the method differ only trivially if at all (Rescher 1977).

Laboratory Experiment 1: End User Understanding

Research Question Addressed

Following completion of field testing, two laboratory experiments were conducted to evaluate the method's effectiveness compared to the standard E-R model and methods previously proposed in the literature. Two separate experiments were required, as evaluating each objective (O₁ and O₂) requires different experimental tasks and sample populations. The first laboratory

experiment evaluated the effectiveness of the method for end-user understanding (O_1). The broad research question addressed was

How effective is the LDM method compared to the standard E-R model and methods previously proposed in the literature for communication with end users?

Justification for Research Method Selection

While action research was an appropriate research method to use when the method was in its developmental phases, it is less suitable once the method had become stable. According to Rescher (1977), successes in actual employment of a method (experiential data) cannot be seen as validated truths but as plausible presumptions. Proof of effectiveness can only be achieved using controlled experiments, which factor out all other variables which may have contributed to the observed outcomes. In the medical field, double-blind experiments or *randomized clinical trials* are routinely used to evaluate the effectiveness of medical treatments—these are considered to be the only permissible evidence that a treatment is effective (Cochrane 1972; Sackett et al. 1997). Surprisingly, however, experiments are rarely used to evaluate the effectiveness of IS design methods. A review of IS design research over the past three decades found that only 1 percent of papers published were experiments (Wynekoop and Russo 1997).

Experimental Design

A four-group, post-test only, between-subjects design was used, with one active factor (representation method). To make the experiment manageable, the number of methods evaluated was limited to the two leading methods proposed in the literature. The two methods chosen were clustered entity models (Feldman and Miller 1986) and structured data models (Simsion 1989). These methods also represent the two predominant paradigms for clustering models: *aggregation* and *generalization*. Participants were first year Accounting students with no prior exposure to E-R modeling. Participants were randomly assigned to groups, trained in the conventions of one of the methods, and given an experimental data model represented using the same method. They were then given a set of questions to answer about the model (*comprehension task*) and a description of user requirements to verify the model against (*verification task*).

Independent Variable

The independent variable had four levels corresponding to the methods being evaluated: standard E-R model (control), leveled data model, clustered entity model, and structured data model.

Dependent Variables

Understanding of the data model was measured using six dependent variables:

- **D1: Comprehension Efficiency.** This was measured by the time taken to complete the comprehension task.
- **D2: Comprehension Effectiveness.** This was measured by the percentage of comprehension questions correctly answered by each subject.
- **D3: Comprehension Efficacy.** This was measured by the number of correct responses on the comprehension test divided by the time taken.
- **D4: Verification Efficiency.** This was measured by the time taken to complete the verification task.
- **D5: Verification Effectiveness.** This was measured by number of discrepancies correctly identified, expressed as a percentage of the total number of discrepancies.

- **D6: Verification Efficacy.** This was measured by the number of discrepancies correctly identified, divided by the time taken to complete the verification task.

Results

The results of the experiment are summarized in Table 1. The cells in the table define the significance of comparisons between the LDM method and each of the other methods on each dependent variable: each cell corresponds to an *a priori* hypothesis. Significance levels in brackets show comparisons that were significant but in the reverse direction to that predicted. Of the 18 hypotheses originally proposed, 9 were supported, 7 were not supported, with reverse findings in 2 cases.

Efficiency. None of the hypotheses relating to the efficiency of the method (comprehension efficiency and verification efficiency) were supported. In fact, the reverse result was found for comprehension efficiency compared to the standard E-R model and the structured data model.

Effectiveness. All hypotheses relating to the effectiveness of the method (comprehension efficiency and verification efficiency) were supported. The LDM representation was found to improve comprehension and verification accuracy compared to the standard E-R model and both competitor methods. The results showed that the method improved comprehension and verification accuracy compared to the standard E-R model by more than 50 percent.

Efficacy. Mixed results were found for the efficacy of the method. All hypotheses relating to verification efficacy were supported while those relating to comprehension efficacy were not supported. In the comprehension task, time taken and accuracy were inversely related, while on the verification task, all groups took around the same time.

Table 1. Hypothesis Testing (ANOVA) Results

| DEPENDENT VARIABLE | vs E-R Model | vs Structured Data Model | vs Clustered Entity Model |
|-----------------------------|--------------|--------------------------|---------------------------|
| Comprehension Efficiency | (.012*) | (.004**) | N/S |
| Comprehension Effectiveness | .005** | .000** | .011* |
| Comprehension Efficacy | N/S | N/S | N/S |
| Verification Efficiency | N/S | N/S | N/S |
| Verification Effectiveness | .003** | .000** | .000** |
| Verification Efficacy | .004** | .000** | .001** |

* Significant at the 0.05 level

**Significant at the 0.01 level

Post hoc testing showed that neither of the methods previously proposed in the literature were superior to the standard E-R model on any of the dependent variables. In fact, the structured data model was found to be inferior on three of the variables (D2, D5, and D6).

Laboratory Experiment 2: Documentation and Maintenance

Research Questions Addressed

The second laboratory experiment evaluated the effectiveness of the method for documentation and maintenance of large data models (O₂). The broad research questions addressed were

1. How effective is the LDM method compared to methods previously proposed in the literature for documentation and maintenance of large data models?
2. What is the likelihood of the method being adopted in practice?

The second research question addresses an issue that is rarely addressed or even considered in IS design research, despite the fact that this is critical for research to have an impact on practice.

Experimental Design

A three-group, post-test only, between-subjects design was used, with one active factor (method used). Participants were final year IS students with extensive experience in E-R modeling. Participants were randomly assigned to one of the groups and trained in one of the methods being evaluated. They were then given an experimental data model in E-R form and asked to document it using the method they had learned. After completing the task, they were asked to complete a post-task survey, which required them to give their perceptions of the method they had used.

Independent Variable

The independent variable had three levels, corresponding to the methods being evaluated: the LDM method and the two leading methods from the literature—the same methods were used as in the first laboratory experiment (clustered entity modeling and structured data modeling). In this experiment, there was no direct comparison to the standard E-R model as the experimental model was itself in E-R form.

Dependent Variables

Three performance-based dependent variables were used to evaluate the methods:

- **D1: Documentation Efficiency.** This was measured by the time taken to complete the documentation task. This provides a measure of efficiency in performing the task.
- **D2: Documentation Correctness.** This was measured by the number of errors in applying the method.
- **D3: Clustering Consistency.** This was measured by the number of clusters produced by each participant expressed as a percentage difference from the mean for the group. This provides a measure of consistency between different people using the method.

Three perception-based variables were also used to evaluate the methods:

- **D4: Perceived Ease of Use.** This was measured using six items on the post-task survey (Questions 1, 4, 5, 9, 11, and 14).
- **D5: Perceived Usefulness.** This was measured using eight items on the post-task survey (Questions 2, 3, 6, 7, 8, 12, 13, and 15).
- **D6: Intention to Use.** This was measured by two items on the post-task survey (Q10 and Q16).

These were used to evaluate the likelihood of the methods being adopted in practice. These constructs were derived from the technology acceptance model (TAM) (Davis et al. 1989), with definitions of constructs modified to reflect the change in domain. While TAM was specifically developed to evaluate user acceptance of computer systems, it is based on a more general theory, the theory of reasoned action (Fishbein and Azjen 1975), which has proven successful in predicting and explaining behavior across a wide variety of domains. This suggests that the constructs of TAM can be adapted to other domains. Items used to operationalize these constructs were adapted from Davis et al.'s (1989) study, with changes in wording to fit use of a method as opposed to use of a computer system.

Results

Comparison of Methods. Table 2 summarizes the results of hypothesis testing. The values in the table represent significance of comparisons between the LDM method and the other two methods on each dependent variable—each cell represents an *a priori* hypothesis. No comparison was possible with the clustered entity model group on documentation correctness because most of the participants were unable to finish the task in the time allowed.

Table 2. Hypothesis Testing (ANOVA) Results

| DEPENDENT VARIABLE | vs Structured Data Model | vs Clustered Entity Model |
|---------------------------|--------------------------|---------------------------|
| Documentation Efficiency | .001*** | .000** |
| Documentation Correctness | .007** | N/A |
| Clustering Consistency | .000** | .002* |
| Perceived Ease of Use | .048** | .000** |
| Perceived Usefulness | N/S | .007** |
| Intention to Use | N/S | .022* |

*Significant at the 0.05 level

**Significant at the 0.01 level

Nine out of 12 hypotheses were supported, with no reverse findings. The group using the LDM method performed significantly better than the clustered entity model group on five dependent variables, and than the structured data model group on three dependent variables. The structured data models group was also superior to the clustered entity model group on two dependent variables (documentation efficiency and perceived ease of use).

Likelihood of Adoption in Practice. Evaluation of likelihood of adoption involved comparing the values of Perceived ease of use, perceived usefulness, and intention to use for each group with the midpoint of the measurement scale (3), to determine whether they were significantly positive (i.e., yes response) or significantly negative (i.e., no response). Table 3 summarizes the results of the one sample t-tests. All comparisons were found to be significantly positive for the LDM method, which suggests that it is highly likely to be adopted in practice.

Table 3. Significance of Responses (One Sample t-test)

| QUESTION | Clustered Entity Model | Structured Data Model | Leveled Data Model |
|-----------------------|------------------------|-----------------------|--------------------|
| Perceived Ease of Use | No (0.031*) | Yes (0.033*) | Yes (0.000**) |
| Perceived Usefulness | N/S | N/S | Yes (0.002**) |
| Intention to Use | N/S | N/S | Yes (0.041*) |

*Significant at the 0.05 level

**Significant at the 0.01 level

Field Experiment: Practitioner Acceptance Testing

Sample Population vs. Target Population

The population from which one selects subjects for an experiment should be representative of the population to which the researcher wishes to generalize results (Cooper and Schindler 1998). Generalizability is a significant problem in experiments involving university students (Babbie 1998). However causal relationships (relationships between variables) are believed to more generalizable across populations than specific characteristics (variable values) (Pedhazur and Schmelkin 1991). This suggests that the findings about the *relative efficacy* of the methods (relationship between independent and dependent variables) in the second laboratory experiment are generalizable to practice, so there is no need to replicate the experiment in its entirety. However we could have little confidence that similar values for perceived ease of use, perceived usefulness, and intention to use would be found with practitioners. As a result, the conclusions about the likelihood of adoption of the LDM method are open to question.

Research Questions Addressed

This experiment represents a partial replication of the second laboratory experiment conducted in a field setting, using a different sample population (experienced data modeling practitioners), using a subset of the dependent variables (those relating to adoption

in practice: D4, D5, and D6) and a single level of the independent variable (the LDM method). The broad research questions addressed by this experiment were

- Is the LDM method likely to be adopted in practice?
- Are the results different from those obtained in the second laboratory experiment?

Research Design

A one-group, post-test only design was used. There were 21 participants, all of whom were experienced data modeling practitioners. They participated voluntarily in the experiment as part of a regular meeting of a professional association. Participants were trained in the LDM method and then given an example E-R model and asked to apply the method to it. Finally, they were asked to complete a post-task survey, in which they were asked to provide their perceptions of the method.

Independent Variable

The independent variable was the method used to represent the data model. In this experiment, it has only a single level (LDM).

Dependent Variables

The dependent variables were the perception-based variables used in the second laboratory experiment: perceived ease of use, perceived usefulness, and intention to use. The same measurement instrument (post-task survey) was used as in the previous experiment. No performance-based data was collected as this is only meaningful in comparison between methods.

Likelihood of Adoption in Practice

One-sample t-tests were conducted on the mean value of each dependent variable to determine whether they were significantly positive or negative (Table 4). All values were found to be significantly positive, which suggests that the method has a very high likelihood of being adopted in practice.

Table 4. Results of Static Comparisons (One Sample t-test)

| DEPENDENT VARIABLE | MEAN | STDEV | SIGNIFICANCE |
|---------------------------|-------------|--------------|---------------------|
| Perceived Ease of Use | 4.64 | 0.43 | .000** |
| Perceived Usefulness | 4.33 | 0.47 | .000** |
| Intention to Use | 4.19 | 0.8 | .000** |

*Significant at the 0.05 level

**Significant at the 0.01 level

Comparison to Laboratory Experiment 2 Results

Comparisons were also carried out between the values of the dependent variables in this experiment and the corresponding group in the second laboratory experiment. As shown in Table 5, practitioners found the method significantly easier to use than the students and also perceived the method to be more useful. No difference was found in participants' intentions to use the method.

Table 5. Differences Between Laboratory Experiment and Field Experiment Results

| CONSTRUCT | LABORATORY EXPERIMENT 2 | FIELD EXPERIMENT | SIGNIFICANCE |
|-----------------------------|-------------------------|------------------|--------------|
| Perceived Ease of Use | 4.16 | 4.64 | .030* |
| Perceived Usefulness | .82 | 4.33 | .040* |
| Intention to Use | 3.61 | 4.19 | 0.08 |

*Significant at the 0.05 level

**Significant at the 0.01 level

Conclusion

This paper has described the development and empirical validation of a method for managing complexity of large data models. A combination of field and laboratory, qualitative and quantitative research methods were used. The results show that the method is generally effective in achieving its objectives (O_1 and O_2) and has a high likelihood of being adopted in practice.

Practical Significance

The practical significance of this research is

- The first laboratory experiment showed that the LDM method significantly improves end-user understanding compared to the standard E-R model. As the E-R model is the most commonly used analysis technique in practice (Davies et al. 2003), improving understanding of such models will help to reduce the level of requirements errors in practice, which are the most common cause of errors in the IS development process and of IS project failure (Martin 1989; Standish Group 1995, 1996).
- The second laboratory experiment and the field experiment showed that the LDM method is highly likely to be adopted in practice, which is an important pragmatic measure of method success and its likely impact on practice (Fitzgerald 1991). Regardless of the potential benefits of IS design methods published, unless they are actually used, these benefits cannot be realized.

Theoretical Significance

The theoretical significance of this research is

- It addresses the problem of ontological incompleteness of the E-R model identified by Wand and Weber (1993) by incorporating constructs for managing complexity.
- It illustrates a systematic approach to validating a method, using a combination of research methods. The combination of a field-based, qualitative method (action research) and traditional hypothesis-testing approaches (laboratory and field experiments) allowed the method to evolve in an iterative manner in its early stages, and then to be subjected to more rigorous testing once it was stable.

General Implications for IS Design Methods

The problem of complexity management is an issue in applying any IS design method in practice. According to Wand and Weber (1993; Weber 1997), constructs for managing complexity are an essential requirement for all IS design methods. The method described in this paper provides a general approach to incorporating complexity management into IS modeling notations. The research thus has general implications for developing more effective IS design techniques. An ontological analysis by Opdahl and Henderson-Sellers (2002) showed that UML also lacks complexity constructs, suggesting that this may be a more widespread problem in IS design methods. Research has recently been completed to apply the representational approach to UML class

diagrams (Moody and Sindre 2003). While the resulting method has yet to be fully tested, the mapping was relatively straightforward and the results of initial empirical testing have been positive.

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