

December 2003

Visual Attention Overload: Representation Effects on Cardinality Error Identification

Cheryl Dunn
Florida State University

Gregory Gerard
Florida State University

Severin Grabski
Michigan State University

Follow this and additional works at: <http://aisel.aisnet.org/icis2003>

Recommended Citation

Dunn, Cheryl; Gerard, Gregory; and Grabski, Severin, "Visual Attention Overload: Representation Effects on Cardinality Error Identification" (2003). *ICIS 2003 Proceedings*. 5.
<http://aisel.aisnet.org/icis2003/5>

This material is brought to you by the International Conference on Information Systems (ICIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ICIS 2003 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

VISUAL ATTENTION OVERLOAD: REPRESENTATION EFFECTS ON CARDINALITY ERROR IDENTIFICATION

Cheryl Dunn

Department of Accounting
Florida State University
Tallahassee, FL USA
cheryl.dunn@fsu.edu

Gregory J. Gerard

Department of Accounting
Florida State University
Tallahassee, FL USA
ggerard@cob.fsu.edu

Severin Grabski

Department of Accounting & Information Systems
Michigan State University
East Lansing, MI USA
grabski@msu.edu

Abstract

Attention overload occurs when people are presented with so many different stimuli that they are unable to adequately direct their cognitive processing to all of the inputs. Visual attention overload is conceptually similar and occurs when people are given visual stimuli in a format that prevents them from effectively processing all of the stimuli. The current study examines whether visual attention overload results in differential performance with conceptual model representations for a task requiring identification of errors in relationship cardinalities.

This study suggests that visual attention management is an important part of cognitive fit. Specifically, a representation that inhibits processing of information because of visual attention overload is not expected to have cognitive fit with a task that requires repeated use and scanning of the same objects that were previously inhibited. This study allows us to move beyond the “spatial representations should be used for spatial tasks” approach to instead attempt to identify the types of tasks that require repeated use of the representations and therefore are likely not to have cognitive fit with a diagram representation if the diagram is sufficiently complex.

Keywords: Data models, system design, visual attention overload, information overload

Introduction

The conventional wisdom is that a picture is worth a thousand words, yet, unless one knows where to look on the picture, the needed information will not be found. This was the basis for many of the studies that identified differences in performance in the tables versus graphs studies. Many studies have subsequently demonstrated that representation format does affect task performance, and that differential performance is a result of cognitive fit, a match between representation format and task (e.g., Dennis and Carte 1998; Dunn and Grabski 2001a; Umanath and Vessey 1994; Vessey 1991, Vessey and Galletta 1991). In low information load conditions (i.e., simple tasks) performance is not affected by representation format (e.g., Umanath 1994); however, in high-load conditions, localization (the required information is available in a single location) enhances performance (Dunn and Grabski 2001a). Many conceptual modeling techniques (e.g., entity-relationship diagrams [ERD], data flow diagrams [DFD], and Unified Modeling Language (UML) diagrams to name just a few) are used to represent complex systems. These

models were developed from an engineering viewpoint, of what information needs to be communicated from the analyst to either the designer or to the user; they were never designed from a cognitive load perspective (indeed, for large projects, the DFDs and ERDs have covered complete walls in the work rooms). A fundamental modeling concern is how much information should be represented since people have limited cognitive resources (e.g., memory and attention). Given the preponderance of use of diagrammatic techniques, if individuals can experience visual attention overload, how can this limitation be overcome?

Visual attention overload is defined as a phenomenon that occurs when a person looks at a representation and the burden is excessive such that their concentration and interpretation of the representation is impaired (Neill and Valdes 1996). In situations of visual attention overload, an individual must selectively attend to the objects of interest (i.e., they exhibit selective attention) and ignore the irrelevant objects. Negative priming occurs when the irrelevant objects become relevant for a subsequent task; the effect is that an individual has more difficulty attending to the now-relevant objects than they did attending to the originally relevant objects (Neill and Valdes 1996). Psychologists have yet to determine whether selective attention results from a facilitated focus on relevant objects or from an inhibition of interfering objects. The negative priming effect suggests that to maintain selective attention it is more important to inhibit interfering objects than to facilitate focused attention.

Although many system analysis and design tasks involve diagrammatic representations that have visually salient qualities, to our knowledge there has been no information systems research on the role of visual attention overload. Visual attention plays a role in all general tasks involving visual stimuli, but in an IS setting it is especially important for reviewers of system documentation. Possible reviewers include IS peer reviews, IS project managers, IS quality control supervisors, IS auditors, and other end users of system documentation. In this paper, we examine the effect of visual attention overload and provide alternatives to overcoming this cognitive limitation in the setting of cardinality error identification within entity-relationship diagrams. We focus on ERDs and cardinality error identification since prior research has examined these constructs (e.g., Bodart et al. 1997; Siau et al. 1997) and they are important constructs that can easily be manipulated and evaluated.

Background and Hypotheses Development

The conceptual model serves as the basis for the database schema that is used to implement a database to meet information needs of intended users. To develop a suitable database schema, the database designer must be able to use the conceptual data model as a communication tool to verify the assumptions made in its creation. Batra and Davis (1992) state that the conceptual model must be capable of providing a structure for the database along with the semantic constraints that can be used to communicate with users. The conceptual data model also serves as a representation of the database after its completion—it is part of the systems documentation, and hence can be used for system evaluation by auditors or others.

Conceptual data models are used to communicate information among designers, analysts, and users. An implicit assumption made is that everyone involved with a particular project can (or will) interpret the diagrams in the same manner. Unfortunately, this is not always the case. Prior research has indicated that expert database modelers do not interpret these diagrams in the same manner as novice modelers. Experts tended to focus on the structural constraints whereas novices tended to focus on the surface semantics (Siau et al. 1997).

A study of evaluators' syntactic and semantic understanding of relationships in entity-relationship diagrams, including minimum participation cardinalities, revealed that fewer mistakes occurred when relationships were evaluated one at a time (i.e., in binary format) than when all relationships were examined in one combined diagram (Dunn and Grabski 2001b). The result was speculated to be the result of the heavier information load (in terms of volume) of the combined diagram. An alternative explanation is that the result was not due to the increased volume of information provided in the combined diagram, but rather was due to visual attention overload caused by the diagram format. To identify cardinality errors in an entity-relationship diagram, an evaluator must selectively attend to each side of each relationship in the diagram. If selective attention is accomplished by inhibition of irrelevant objects, it will be more difficult to selectively attend to an object that was previously inhibited.

Attention is said to involve the transfer of information from sensory to short-term memory and is assumed to be a critical mental resource necessary for the operation of any conscious or partly conscious process. Theories of attention assume it is a limited mental resource and the upper limits of this resource pool determine how many separate processes can occur simultaneously (Ashcraft 1994). Attention modulates sensory activity only when sensory systems are overloaded (Luck et al. 2000). This implies that attention management mechanisms for the use of diagrammatic representations are only needed for diagrams that overload the visual attention capacity of the user, and also explains why simple tasks or low information load tasks do not result in representation-driven performance differences (e.g., Umanath 1994). We refer to this phenomenon, in which a person looks at

a representation and the burden is excessive such that his or her concentration and interpretation of the representation is impaired, as visual attention overload. Visual attention overload is a special case of information overload, as visual inputs are a form of information. In situations of overload, people must selectively attend to the objects of interest. Psychologists are unsure whether selective attention is the result of facilitation of focus on relevant objects or of inhibition of interfering objects. Regardless of whether attention results from the focus on relevant objects or the inhibition of interfering objects, overload in information system representations may occur. If overload exists, then determination as to whether an alternative representation will overcome the overload is critical.

A theory of facilitative attention management is the spatial attention *aperture* metaphor (Pan and Eriksen 1993). This theory suggests attention is applied to the objects of interest as a “spotlight” that highlights the relevant objects for a particular task; thus attention is managed by the facilitation of focus. In the case of validating an ERD, this would be consistent with providing an evaluator a binary set of entities and the associated cardinality information in a single relationship. The focus is only on that set, and each subsequent set is a new set with a spotlight on the relevant information.

An alternative theory suggests attention is managed by the inhibition of objects that are not of interest in order to free up resources to concentrate on objects of interest. This theory arose because of the observation of a phenomenon called negative priming (Neill and Valdes 1996). Negative priming is the occurrence in which objects in a visual representation that were irrelevant (and thus ignored) for one task become relevant for a subsequent task but are still ignored. Such a phenomenon would indicate the inhibition of interfering objects is more important in attention than is facilitation. The example most commonly used to explain negative priming is found in the first study to demonstrate the phenomenon (Dalrymple-Alford and Budayr 1966) using a version of the Stroop Color and Word Test (Stroop 1935). People who take the Stroop test are required to name the ink color in which words are written as quickly as possible. The “Stroop effect” finds that naming the ink color for a word that represents a different color (e.g., the word GREEN written in red ink) is more difficult than naming the ink color for non-color words. Negative priming results when the color word (which the person had to suppress in order to name the ink color) is used as the ink color for the next word (e.g., if the word GREEN written in red ink is followed by the word BLUE written in green ink). Thus, negative priming occurs when there is a prime trial in which the person must respond to a prime target and avoid responding to a prime distractor, followed by a probe trial in which the person must respond to a probe target that is related (or identical) to the prime distractor. Negative priming is defined as slower or less accurate responding to related probe targets as compared with unrelated probe targets (Neill and Valdes 1996). In the validation of an ERD, this would be consistent with the presentation of a complex diagram in which an evaluator needs to focus on a relationship set that requires the suppression of distracting cardinality relationship sets that exist with the first entity pairs. When the evaluator subsequently attempts to evaluate the suppressed relationships, negative priming occurs, resulting in errors.

To demonstrate that decreased evaluator performance with combined diagram representations as compared to binary diagram representations results from visual attention overload and negative priming, several conditions must be met. First, the performance difference must be demonstrated to exist; that is, more mistakes should be made in identifying errors in participation cardinalities with a full diagram representation than with the same relationships presented one at a time. Therefore, H1 is proposed to demonstrate this first condition is met.

H1: More mistakes will be made in identifying errors in participation cardinalities using a full diagram representation as compared to a binary diagram representation, controlling for cardinality knowledge.

Second, there must be evidence that the greater number of mistakes made was due to inhibited processing of objects on the representation. For example, mistakes made in identifying cardinalities that are of “illegal syntax” would likely be due to a failure to process those cardinalities. H2 is proposed to demonstrate this second condition is met.

H2: More mistakes will be made in identifying illegal syntax errors in participation cardinalities using a full diagram representation as compared to a binary diagram representation, controlling for cardinality knowledge.

Third, the alternative explanation of the performance difference resulting only from the increased volume must be ruled out. In order to rule out this explanation, an alternative form of ER model representation that is informationally equivalent to the diagram form must be evaluated. The Backus-Naur Form (BNF) grammar format has been proposed for entity-relationship models as informationally equivalent to the diagram format (Batini et al. 1992). Figure 1 illustrates an acquisition cycle entity-relationship model in diagram format; Figure 2 illustrates the same entity-relationship model in grammar format; Figure 3, Panel A shows an example entity-relationship model in binary diagram format, with Panel B showing an example entity-relationship model in binary

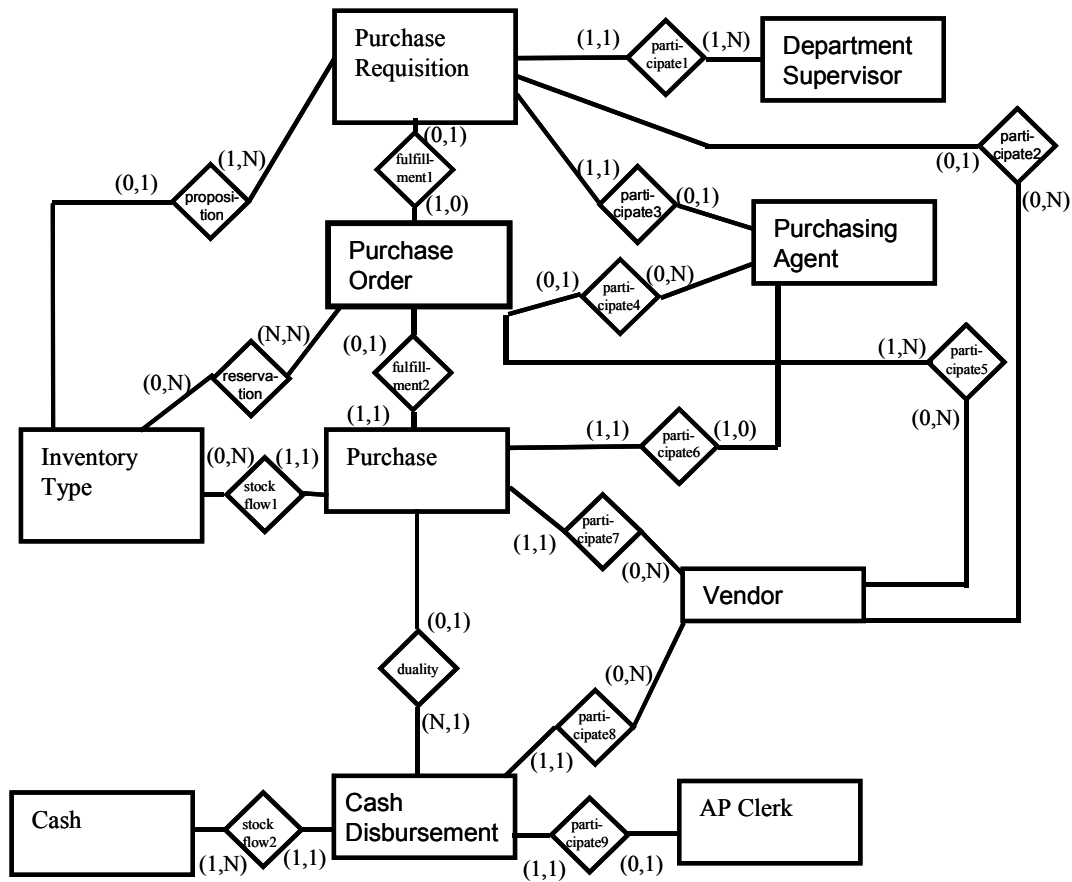


Figure 1. Acquisition Cycle ER Model in Diagram Format

grammar format. Exactly the same information is contained in both representations; only the formatting is different. To rule out the effects noted in testing H1 and H2 as being caused purely by the increased volume of information in the full diagram representation, no performance differences should be observed between the full grammar representation as compared to an equivalent set of binary grammar representations. H3a and H3b are proposed to rule out this alternative explanation.

- H3a: No difference in mistakes made in identifying errors in participation cardinalities will be observed for a full grammar representation as compared to a binary grammar representation, controlling for cardinality knowledge.
- H3b: No difference in mistakes made in identifying illegal syntax errors in participation cardinalities will be observed for a full grammar representation as compared to a binary grammar representation, controlling for cardinality knowledge.

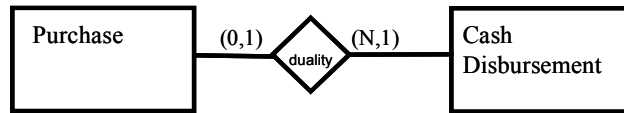
Research Method

A laboratory experiment was conducted to test these hypotheses, with 87 graduate students and 113 undergraduate students enrolled in information systems courses serving as participants. Although these were different courses at two different universities, for all students it was their first information systems course. The courses contained content related to this study and were taught by the same instructor. As part of the students' course work, they were taught entity-relationship modeling in both diagram and grammar formats. They were held accountable for interpreting both representation formats on exams, but could choose whether to create conceptual models in diagram or grammar format. Most chose to create conceptual models in diagram format on exams. The participants completed the error identification tasks as an in-class exercise and were graded for the exercise based on accuracy and received class credit for participation. Participants completed error identification tasks with respect to the cardinalities on a set of 16 relationships into which errors had been seeded.

Entity:	Accounts Payable Clerk
Entity:	Department Supervisor
Entity:	Cash
Entity:	Cash Disbursement
Entity:	Inventory Type
Entity:	Purchase
Entity:	Purchase Order
Entity:	Purchase Requisition
Entity:	Purchasing Agent
Entity:	Vendor
Relationship:	Duality
Connected Entities:	(0,1) Purchase (N,1) Cash Disbursement
Relationship:	Fulfillment1
Connected Entities:	(1,0) Purchase Order (0,1) Purchase Requisition
Relationship:	Fulfillment2
Connected Entities:	(1,1) Purchase (0,1) Purchase Order
Relationship:	Participate1
Connected Entities:	(1,1) Purchase Requisition (1,N) Department Supervisor
Relationship:	Participate2
Connected Entities:	(0,1) Purchase Requisition (0,N) Vendor
Relationship:	Participate3
Connected Entities:	(1,1) Purchase Requisition (0,1) Purchasing Agent
Relationship:	Participate4
Connected Entities:	(0,1) Purchase Order (0,N) Purchasing Agent
Relationship:	Participate5
Connected Entities:	(1,N) Purchase Order (0,N) Vendor
Relationship:	Participate6
Connected Entities:	(1,1) Purchase (1,0) Purchasing Agent
Relationship:	Participate7
Connected Entities:	(1,1) Purchase (0,N) Vendor
Relationship:	Participate8
Connected Entities:	(1,1) Cash Disbursement (0,N) Vendor
Relationship:	Participate9
Connected Entities:	(1,1) Cash Disbursement (0,1) AP Clerk
Relationship:	Proposition
Connected Entities:	(1,N) Purchase Requisition (0,1) Inventory Type
Relationship:	Reservation
Connected Entities:	(N,N) Purchase Order (0,N) Inventory Type
Relationship:	Stockflow1
Connected Entities:	(1,1) Purchase (0,N) Inventory Type
Relationship:	Stockflow2
Connected Entities:	(1,N) Cash (1,1) Cash Disbursement

Figure 2. Acquisition Cycle ER Model in Grammar Format

Panel A: Binary ER Model Relationship



(Note: The relationships were presented two to a page, with a horizontal line drawn through the center of the page.)

Panel B: Binary Grammar Model Relationship

Entity: Cash Disbursement

Entity: Purchase

Relationship: Duality

Connected Entities: (0,1) Purchase
(N,1) Cash Disbursement

(Note: The relationships were presented two to a page, with a horizontal line drawn through the center of the page.)

Figure 3. Sample Binary Presentation of the Acquisition Cycle

Variables

Information load served as the independent variable, with two levels. Relationships were either presented one at a time (binary condition) or combined into a complete entity-relationship model (full condition). Participants were randomly assigned to complete revenue cycle tasks or acquisition cycle tasks. The tasks were designed to be equivalent for both cycles and no significant performance differences were observed between cycles.

The dependent variable (MISTAKE) for H1 was the number of total mistakes made in identifying seeded errors in the relationships. If a seeded error was not identified, it was counted as a mistake. The dependent variable (ILLEGAL MISTAKE) for H2 was the number of mistakes made in identifying seeded illegal errors in the relationships. To develop the grading scale, an expert who was blind to the research question was asked to identify cardinality errors in each of the relationships. The expert is an information systems professor who has been teaching conceptual modeling for more than 20 years. The expert identified and classified the errors as illegal, illogical, or debatable. Illegal errors were those that are not allowed in participation cardinalities. For example, an entity is not allowed to have minimum participation in a relationship of many—the only legal values are zero and one (although a minimum cardinality greater than 1 may be appropriate for some situations, these participants had been taught that the only legal values for minimum cardinalities are zero and one). Similarly an entity is not allowed to have maximum participation in a relationship of zero (only one and many are valid). Some of the seeded errors were illegal cardinalities; others were illogical cardinalities. Illogical errors were those that do not make sense according to common business practice. For example, maximum participation of a salesperson in a relationship with sale should be many rather than one. A one maximum would indicate that the enterprise has forbidden its salespeople to make more than one sale. To allow for at least one of its salespeople to make more than one sale, the maximum would have to be indicated as many. The expert classified as debatable those errors that were illogical for most common business enterprises but for which exceptions are reasonable. We count only mistakes classified as illegal or illogical. All participants demonstrated an understanding that a minimum cardinality cannot be N and that a maximum cardinality cannot be 0. Any of the illegal seeded errors not identified may be assumed to result from inhibited processing of those cardinalities; they didn't pay attention to them.

Participants' knowledge of cardinalities was included as a co-variate. Cardinality knowledge was measured as participants' score on a set of multiple choice questions that tested their ability to identify either the correct cardinality notation to correspond to a narrative or the correct narrative to correspond to cardinality notation.

Materials

Participants were instructed to examine the entity-relationship model and identify all cardinality errors by circling each incorrect minimum and/or maximum cardinality and writing in the correct cardinality. They were instructed to leave unmarked any cardinality they believed was correct. The following key points were emphasized in the instructions:

- This model is only one part of an enterprise-wide model, that is, some of the entities in this model may also be part of other business processes in the enterprise-wide model.
- For relationships between an internal agent and an event, assume there is never an alternative internal agent performing the same function with respect to that event. There may be an additional internal agent performing a different function and therefore participating in a different relationship with that event.
- All inventory is catalog style inventory (as opposed to specifically identified inventory) and therefore is called inventory type.
- No unreasonable/irrational business policies should be assumed.
- Some relationships may contain multiple cardinality errors; some relationships may contain just one cardinality error; some relationships may contain zero cardinality errors.

Results of Statistical Tests

The preferred statistical test for evaluating nonnegative, count-dependent variables is the poisson regression (Cameron and Trivedi 1998; Long 1997). However, if the data are overdispersed (as indicated by a variance greater than the mean), then the negative binomial regression model is considered more appropriate (Cameron and Trivedi 1998; Long 1997). The regression model tested for H1 (for diagram format users) is

$$\text{MISTAKE} = \alpha + \beta_1 \text{BINARY} + \beta_2 \text{CARDINALITY KNOWLEDGE} + \epsilon$$

For H1 the poisson regression revealed overdispersion in the data, therefore negative binomial regression model results are reported in Table 1, Panel A.

The expectation was that users of the ERD in binary format would make significantly fewer mistakes in identifying seeded cardinality errors than would users of the diagram in full format. The regression results support H1. The coefficient on BINARY is negative, indicating that binary format users made fewer mistakes than full format users. The difference is significant at $p < .002$ (one-tailed). Binary diagram users made 83 mistakes whereas full diagram users made 145 mistakes. Table 1, Panel A also reveals that participants' cardinality knowledge was significant; the greater their knowledge, the fewer mistakes made ($p < .006$, one-tailed).

The regression model tested for H2 (for diagram format users) is

$$\text{ILLEGAL MISTAKE} = \alpha + \beta_1 \text{BINARY} + \beta_2 \text{CARDINALITY KNOWLEDGE} + \epsilon$$

For H2, the poisson regression model did not reveal overdispersion in the data; the poisson results are reported in Table 1, Panel B. The expectation was that users of the ERD in binary format would make significantly fewer mistakes in identifying illegal seeded cardinality errors than would users of the diagram in full format. The regression results support H2. The coefficient on BINARY is negative; binary format users made less mistakes than did full format users. Binary diagram users made only 6 illegal mistakes whereas full diagram users made 23 illegal mistakes ($p < .002$ one-tailed). Table 1, Panel B also reveals that participants' cardinality knowledge was not significant; that was expected since all participants demonstrated knowledge that minimum cardinalities can't be N and maximum cardinalities couldn't be 0.

The regression model tested for H3a (for grammar format users) is

$$\text{MISTAKE} = \alpha + \beta_1 \text{BINARY} + \beta_2 \text{CARDINALITY KNOWLEDGE} + \epsilon$$

For H3a, the poisson regression revealed overdispersion; the negative binomial regression results are presented in Table 2, Panel A. The expectation was for no difference in the number of mistakes made by users of the ER grammar in binary versus full formats. H3a cannot be rejected. Full format grammar users made approximately the same number of mistakes (105) as binary format grammar users (102) ($p < .993$, two-tailed). Table 2, Panel A also shows that participants' cardinality knowledge was significant; the greater their knowledge, the fewer mistakes they made ($p < .004$ one-tailed).

The regression model tested for H3b (for grammar format users) is

$$ILLEGAL\ MISTAKE = \alpha + \beta_1BINARY + \beta_2CARDINALITY\ KNOWLEDGE + \epsilon$$

For H3b, the poisson regression did not reveal overdispersion; the poisson regression results are presented in Table 2, Panel B. The expectation was for no difference in the number of illegal mistakes made by users of the ER grammar in binary versus full formats. H3b cannot be rejected. Full format grammar users made approximately the same number of illegal mistakes (12) as binary format grammar (9) users ($p < .561$, two-tailed). Table 2, Panel B also shows that participants' cardinality knowledge was not a significant determinant of their performance.

Table 1. Regression Model for Diagram Format Variables

PANEL A

Negative Binomial Regression Model for Diagram Format Variables Predicting Mistakes

$$MISTAKE = \alpha + \beta_1BINARY + \beta_2CARDINALITY\ KNOWLEDGE + \epsilon$$

<i>Independent Variable</i>	<i>Coefficient</i>	<i>Standard Error</i>	<i>Two-tailed p-value</i>
BINARY	-0.539	0.183	0.003
CARDINALITY KNOWLEDGE	-0.216	0.086	0.012

Note: N = 98.

PANEL B

Poisson Regression Model for Diagram Format Variables Predicting Illegal Mistakes

$$ILLEGAL\ MISTAKE = \alpha + \beta_1BINARY + \beta_2CARDINALITY\ KNOWLEDGE + \epsilon$$

<i>Independent Variable</i>	<i>Coefficient</i>	<i>Standard Error</i>	<i>Two-tailed p-value</i>
BINARY	-1.361	0.461	0.003
CARDINALITY KNOWLEDGE	-0.081	0.168	0.629

Note: N = 98.

Where

MISTAKE	number of mistakes made
ILLEGAL MISTAKE (DV)	number of illegal mistakes made
BINARY	dummy variable scored 1 for binary series of relationships, 0 for full depiction of relationships
CARDINALITY KNOWLEDGE	score on a set of multiple choice questions used to assess cardinality knowledge

Table 2. Regression Model for Grammar Format Variables**PANEL A:****Negative Binomial Regression Model for Grammar Format Variables Predicting Mistakes**

$$MISTAKE = \alpha + \beta_1 BINARY + \beta_2 CARDINALITY KNOWLEDGE + \varepsilon$$

<i>Independent Variable</i>	<i>Coefficient</i>	<i>Standard Error</i>	<i>Two-tailed p-value</i>
BINARY	0.002	0.225	0.993
CARDINALITY KNOWLEDGE	-0.301	0.112	0.007

Note: N = 102.

PANEL B:**Poisson Regression Model for Grammar Format Variables Predicting Illegal Mistakes**

$$ILLEGAL MISTAKE = \alpha + \beta_1 BINARY + \beta_2 CARDINALITY KNOWLEDGE + \varepsilon$$

<i>Independent Variable</i>	<i>Coefficient</i>	<i>Standard Error</i>	<i>Two-tailed p-value</i>
BINARY	-0.257	0.442	0.561
CARDINALITY KNOWLEDGE	-0.175	0.198	0.375

Note: N = 102.

Where

MISTAKE	number of mistakes made
ILLEGAL MISTAKE (DV)	number of illegal mistakes made
BINARY	dummy variable scored 1 for binary series of relationships, 0 for full depiction of relationships
CARDINALITY KNOWLEDGE	score on a set of multiple choice questions used to assess cardinality knowledge

Implications of Results and Future Research Directions

This study contributes to the psychology and information systems literatures. Psychology researchers have observed the negative priming effect for simple identification tasks (that take only milliseconds to complete) requiring selective attention. We demonstrate that this phenomenon persists in a task requiring more cognitive processing than does simple identification, and that it affects accuracy, indicating additional support for the inhibition view of selective attention in cases of visual attention overload. Prior information systems studies that examined representation formats from the stance of cognitive fit have demonstrated that information load affects whether cognitive fit matters. The current study helps explain why this phenomenon has been observed and affirms the role of attention management in cognitive fit.

The purpose of this study was not to compare diagram and grammar representations; it was to further our understanding of the use of representations. The grammar representation was needed to rule out the possible information volume explanation. However, for the study to have practical implications, such a comparison is desirable. The study's results of the hypothesis tests reveal that diagram representations containing 10 entities and 16 relationships result in visual attention overload as indicated by negative priming for the task of participation cardinality error identification. Such a diagram would be considered relatively small and simple in practice.

One implication is that entity-relationship diagrams should be presented in binary format. However, benefits of a combined model may exist in the form of being able to see relationship synergies. For example, if an event could be handled by a manager or a clerk, and the manager and clerk are represented as separate entities, viewing separate relationships may lead to changing the zero minimum participation on the event to one when it really should be zero; whereas if both relationships are viewed simultaneously, the evaluator may realize that the minimum participation should be zero. In this study, we controlled for this situation by specifying in the instructions that only one type of internal agent participates with each event. In practice, however, this cannot be controlled or assumed away.

Table 3. Regression Model for Treatment Group Variables

PANEL A:

Negative Binomial Regression Model for Treatment Group Variables Predicting Mistakes

$$MISTAKE = \alpha + \beta_1BINARYDIAGRAM + \beta_2BINARYGRAMMAR + \beta_3FULLGRAMMAR + \beta_4CARDINALITY KNOWLEDGE + \epsilon$$

<i>Independent Variable</i>	<i>Coefficient</i>	<i>Standard Error</i>	<i>Two-tailed p-value</i>
INTERCEPT (FULLDIAGRAM)	1.860	0.251	<0.001
BINARYDIAGRAM	-0.535	0.204	0.009
BINARYGRAMMAR	-0.453	0.199	0.023
FULLGRAMMAR	-0.451	0.198	0.023
CARDINALITY KNOWLEDGE	-0.256	0.070	<0.001

Note: N = 200.

PANEL B:

Poisson Regression Model for Treatment Group Variables Predicting Illegal Mistakes

$$ILLEGAL MISTAKE = \alpha + \beta_1BINARYDIAGRAM + \beta_2BINARYGRAMMAR + \beta_3FULLGRAMMAR + \beta_4CARDINALITY KNOWLEDGE + \epsilon$$

<i>Independent Variable</i>	<i>Coefficient</i>	<i>Standard Error</i>	<i>Two-tailed p-value</i>
INTERCEPT (FULLDIAGRAM)	-0.382	0.422	0.366
BINARYDIAGRAM	-1.349	0.460	0.003
BINARYGRAMMAR	-1.006	0.393	0.011
FULLGRAMMAR	-0.740	0.357	0.038
CARDINALITY KNOWLEDGE	-0.119	0.127	0.348

Note: N = 200.

Where:

MISTAKE	number of mistakes made
ILLEGAL MISTAKE	number of illegal mistakes made
CARDINALITY KNOWLEDGE	score on a set of multiple choice questions used to assess cardinality knowledge
BINARYDIAGRAM	dummy variable scored 1 for binary diagram treatment group, 0 otherwise
BINARYGRAMMAR	dummy variable scored 1 for binary grammar treatment group, 0 otherwise
FULLGRAMMAR	dummy variable scored 1 for full grammar treatment group, 0 otherwise
FULLDIAGRAM	intercept term (i.e., when BINARYDIAGRAM, BINARYGRAMMAR, and FULLDIAGRAM all equal 0)

Rather than only providing binary relationships, another possibility suggested by this study is to provide full ERDs in grammar format. Such a representation was revealed by H3 not to result in visual attention overload. Users did equally well with binary and full grammar formats. The question then becomes whether users perform as well with the grammar format as with the binary diagram format. Although these users were trained in both the diagram and grammar formats, most chose to use the diagram format when creating conceptual models. If performance is better with diagrams than with grammar, then it would be difficult to say whether the increased performance is due to more practice with the diagram representation preference for diagrams. To evaluate this issue, two additional regression models were tested. Results for these regressions are shown in Table 3. The first regression model run was:

$$MISTAKE = \alpha + \beta_1BINARYDIAGRAM + \beta_2BINARYGRAMMAR + \beta_3FULLGRAMMAR + \beta_4CARDINALITY KNOWLEDGE + \epsilon$$

FULLDIAGRAM users form the intercept term. The negative coefficients and significance of the difference for BINARYDIAGRAM, BINARYGRAMMAR, and FULLGRAMMAR indicate that users in each of these three groups made significantly fewer mistakes than did users in the FULLDIAGRAM group. *Post hoc* tests revealed no difference between BINARYDIAGRAM and BINARYGRAMMAR ($p < .70$), BINARYDIAGRAM and FULLGRAMMAR ($p < .69$), and BINARYGRAMMAR and FULLGRAMMAR ($p < .99$). Analysis of illegal mistakes required a second regression:

$$\text{ILLEGAL MISTAKE} = \alpha + \beta_1\text{BINARYDIAGRAM} + \beta_2\text{BINARYGRAMMAR} + \beta_3\text{FULLGRAMMAR} + \beta_4\text{CARDINALITY KNOWLEDGE} + \epsilon$$

Again, FULLDIAGRAM forms the intercept term. The negative coefficients and significance of the difference for BINARYDIAGRAM, BINARYGRAMMAR, and FULLGRAMMAR indicate that users in each of these groups made significantly fewer illegal mistakes than did users in the FULLDIAGRAM group. *Post hoc* tests revealed no difference between BINARYDIAGRAM and BINARYGRAMMAR ($p < .52$), BINARYDIAGRAM and FULLGRAMMAR ($p < .23$), BINARYGRAMMAR and FULLGRAMMAR ($p < .55$). These results imply that providing a full grammar representation of an entity-relationship model may be preferable to providing a full diagram representation of the same entity-relationship model for the purpose of identifying cardinality errors. Users performed equally well with the full grammar format as they did with either the binary diagram or the binary grammar formats, and they performed significantly better than with the full diagram format. This study does not claim that is the ideal solution. Other means may be available for mitigating the visual attention overload, while preserving the ability to view relationship synergies.

The question of “how complex is complex enough to result in attention overload and negative priming” has not been addressed in this study. Future research is needed to delve further into the cognitive processes surrounding error identification tasks. Additional research is also needed to identify whether other types of tasks result in visual attention overload with diagram representations. This study suggests that attention management is an important part of cognitive fit. Specifically, a representation that inhibits processing of information because of attention overload is not expected to have cognitive fit with a task that requires repeated use and scanning of the same objects that were previously inhibited. This study allows us to move beyond the “spatial representations should be used for spatial tasks” approach to instead attempt to identify the types of tasks that require repeated use of the representations and therefore are likely not to have cognitive fit with a diagram representation if the diagram is sufficiently complex.

References

- Ashcraft, M. H. *Human Memory and Cognition* (2nd ed.), HarperCollins College Publishers, New York, 1994.
- Batra, D., and Davis, J. G. “Conceptual Data Modeling in Database Design: Similarities and Differences between Expert and Novice Designers.” *International Journal of Man-Machine Studies* (37), 1992, pp. 83-101.
- Batini, C., Ceri, S., and Navathe S. B. *Conceptual Database Design: An Entity Relationship Approach*, Benjamin/Cummings, Redwood City, CA, 1992.
- Bodart, F., Patel, A., Sim, M., and Weber, R. “Should Optional Properties be Used in Conceptual Modeling? A Theory and Three Empirical Tests,” *Information Systems Research* (12:4), December 2001, pp. 384-405.
- Cameron, A. C., and Trivedi, P. K. *Regression Analysis of Count Data*, Cambridge University Press, New York, 1998.
- Dalrymple-Alford, E. C., and Budayr, B. “Examination of Some Aspects of the Stroop Color-Word Test,” *Perceptual and Motor Skills* (23), 1966, pp. 1211-1214.
- Dennis, A. R., and Carte, T. A. “Using Geographical Information Systems for Decision Making: Extending Cognitive Fit Theory to Map-Based Presentations,” *Information Systems Research* (9:2), June 1998, pp. 194-203.
- Dunn, C. L., and Gerard, G. J. “Auditor Efficiency and Effectiveness with Diagrammatic and Linguistic Conceptual Model Representations,” *International Journal of Accounting Information Systems* (2), 2001, pp. 223-248.
- Dunn, C. L., and Grabski, S. V. “An Investigation of Localization as an Element of Cognitive Fit in Accounting Model Representations,” *Decision Sciences* (32:1), Winter, 2001a, pp. 44-94.
- Dunn, C. L., and Grabski, S. V. “Syntactic and Semantic Understanding of Conceptual Data Models,” in *Proceedings of the 22nd International Conference on Information Systems*, V. Storey, S. Sarkar, and J. I. DeGross (eds.), New Orleans, LA, 2001b, pp. 107-108.
- Long, S. *Regression Models for Categorical and Limited Dependent Variables*, Sage Publications, Thousand Oaks, CA, 1997.
- Luck, S. J., Woodman, G. F., and Vogel, E. K. “Event-Related Potential Studies of Attention,” *Trends in Cognitive Sciences* (4), 2000, pp. 432-440.

- Neill, W. T., and Valdes, L. A. "Facilitatory and Inhibitory Aspects of Attention," Chapter 3 in *Converging Operations in the Study of Visual Selective Attention*, A. F. Kramer, M. G. H. Coles, and G. D. Logan (eds.), American Psychological Association, Chicago, 1996, pp. 77-106.
- Pan, K., and Eriksen, C. W. "Attentional Distribution in the Visual Field During *Same-Different* Judgments as Assessed by Response Competition," *Perception and Psychophysics* (53), 1993, pp. 134-144.
- Siau, K., Wand, Y., and Benbasat, I. "The Relative Importance of Structural Constraints and Surface Semantics in Information Modeling," *Information Systems* (22:2/3), 1997, pp. 155-170.
- Stroop, J. R. "Studies of Interference in Serial Verbal Reactions," *Journal of Experimental Psychology* (18), 1935, pp. 643-662
- Umanath, N. "Effect of IS Variables on Information Acquisition Modes: An Experimental Investigation." *Information & Management* (27:5), November 1994, pp. 287-302.
- Umanath, N., and Vessey, I. "Multiattribute Data Presentation and Human Judgment: A Cognitive Fit Perspective." *Decision Sciences* (25:5/6), September/December 1994, pp. 795-824.
- Vessey, I. "Cognitive Fit: A Theory-Based Analysis of the Graph Versus Tables Literature," *Decision Sciences* (22), 1991, pp. 219-240.
- Vessey, I., and Galletta, D. "Cognitive Fit: An Empirical Study of Information Acquisition," *Information Systems Research* (2:1), March 1991, pp. 63-84.