Does construct overload truly overload the performance?

- An experimental study of experienced data modeler.

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ABSTRACT

A principal activity in information systems development involves building a conceptual model of domain that an information system is intended to support. Such models are created using a conceptual-modeling grammar fundamental means to specifying information systems requirement. However, the actual usage of grammar is poorly understood and some issues regarding conceptual grammar such as construct overload still remain unsolved. With regard to construct overload in conceptual modeling, past studies have had some deficiencies in research methods and even have presented contradicting results. In this paper, we experimented to test whether construct overload enables conceptual models users to understand a domain more efficiently. To acquire a more complete and accurate understanding of construct overload, our study focused on three major points; the evaluation of conceptual modeling grammar semantics, research participants and domain familiarity. This paper's key contribution is that it is one of the first studies to investigate practitioner's aspects of construct overload employing different degrees of domain familiarity by investigating the cognitive processes of practitioner. In addition, this research reconciles conflicting outcomes by examining practical directions for model variation. The result of study will broaden the perspective on usability in the context of the conceptual model and may serve as an ontological guidance to construct overload when modelers create a conceptual model.

Keywords: Conceptual Modeling, Conceptual Model Grammars, Construct Overload, Domain Familiarity, Domain Knowledge, Empirical Research, Entity Relationship Diagram (ERD), Information Systems Development, Ontological Clarity, Protocol Analysis, Neuroscience Methods

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1. Introduction

An information system is a representation of a real world system (Wand and Weber, 1995). For many years, an information system has supported documenting the common understanding about real world domain (Recker et al., 2011). This documentation often takes form of conceptual models (Maes and Poels, 2007). Conceptual models builds a “representation of selected semantics” of a domain (Weber 2003, p.1) resulting conceptual models capture the essence of domain and represent it in terms of specific constructs (Story, 2017). A quality conceptual model is evaluated by domain ontology expressed in a conceptual modeling grammar (Burton-Jones and Weber, 2014). Nonetheless, many conceptual models lack an adequate specification of the semantics embodied in conceptual modeling grammars, leading to inconsistent interpretations and uses of knowledge (Grüninger et al., 2000; Clarke et al., 2016; Story, 2017).

Theory regarding conceptual modeling grammar is proposed to deliver better and consistent understating and to specify the requirements of model, however, it also produced some counterintuitive and controversial results (Clarke et al., 2016; Suh and Park, 2017). In detail, studies related to construct overload, especially the part-whole relationship, against the argument of theory of ontological clarity indicating constructs of conceptual grammar exist in bijective correspondence with the constructs of an ontology presented the inconsistent results. In detail, Shanks et al. (2008) concluded that the bijective correspondence model allows user to better understand a domain, which indicates that a distinction needs to be made between an entity and a relationship. However, Allen and March (2012) came to the opposite conclusion of Shanks et al. (2008) and argued that no distinction is needed between an entity and a relationship. These conflicting viewpoints were published in the same issue of *MIS Quarterly* in September 2012 and the representation of the part-whole relation as a relationship or an entity remains an issue to be resolved. In this paper, we empirically examine the relationship between construct overload in conceptual model and user performance. Therefore, the research question is: *Does construct overload affect the user’s performance?*

In an attempt to answer the above question, we examined research method of two previous studies, Shanks et al., 2008 and Allen and March, 2012, and then performed the experiment to reduce the potential confounding effects from prior research by complementing theoretical background and methodologies. Our study focus on three major points; evaluation of semantics of conceptual modeling grammar, research participants and domain familiarity. First, evaluation of semantics of conceptual modeling grammar is mostly based on theory of ontological clarity achieved only when the mapping between a set of conceptual modeling construct and a set of ontological construct is isomorphic (Shanks et al., 2008; Suh and Park, 2017). Theory of ontological clarity, however, is rooted in computational and algorithmic theories rather than neurophysiological theories of human visual object recognition systems and linguistics theories of human understanding of relations between syntactic and semantic processing. There is point to articulating other theories to evaluate the semantics of conceptual modeling if computational and algorithmic theories lead to inconsistency and imprecision.

Second, in conceptual modeling research, the majority of laboratory experiments used students as research participants (compeau et al., 2012). Both studies were performed using industry workers who do not have modeling experience as research participants (Skanks et al., 2008) and students majoring in management information systems (MIS) (Allen and March, 2012). This can cause flawed conclusions due to the difference between the actual users of conceptual model and the survey participants. Unlike other research, it is hard to assert that the major user of conceptual modeling is the students, even they learned some courses related to Information Systems (Sears, 1986; Davis et al., 2005). The practitioners who still embraced conceptual modeling, such as communicating with the developer, identifying the domain, and improving modeling method and script, could be the actual user of the conceptual model (Davis et al., 2005; Suh and Park, 2017). There is point to studying modeling expert (we call them practitioners) as research subjects to understand the actual the usage of the conceptual model. (Larkin et al., 1980; Glaser and Farr, 1988; Batran and Davis, 1992).

Third, the domain familiarity refers to people's level of existing knowledge about a given topic or domain (Glenberg and Epstein, 1987; Shanks and Serra, 2014; Suh and Park 2017), and is the knowledge of the area to which a set of theoretical concepts is applied (Khatri et al. 2006). If a person is familiar with a certain domain, he or she has a high level of knowledge about that domain. Therefore, people’s domain familiarity is predictive of performance on tasks related to the topic(s) about which they possess either high or low knowledge levels (Feltovich et al., 2006; Shanks and Serra, 2014). Both conceptual modeling research described above used the domain of project-planning for Shanks et al. (2008) and the Collaborative Auditing Incorporated (CAI) for Allen and March (2012), which is familiar to the user. However, this can lead to problems because it is hard to exclude user domain knowledge when a user interprets the conceptual model in a different domain (Suh and Park, 2017). In such cases, it is difficult to measure the exact effect of a domain because of the lack of comparisons where the model domain is unfamiliar to the user. There is point to conducting the experiment with unfamiliar domain in which domain knowledge is less influenced.

This paper’s key contribution is that it is one of the first to investigate practitioner’s aspects of construct overload employing different degrees of domain familiarity by investigating practitioner cognitive process. In addition, this research reconciles conflicting outcomes and acquire more complete and accurate understanding of construct overload by examining practical directions for model variation.

The remainder of this article proceeds as follows. The next section offers the research background of the study, including the theoretical background. The third section provides the rationale for the proposition we tested empirically. The fourth section describes the empirical method and related results. The fifth section presents cognitive process tracing study to results of experiment. The last section discusses some implications of the results for practical application as well as research and some limitations.

2. Theory and Related Work

The basic concept this study delivers is construct overload. Figure 1 and 2 present two examples of how construct overload (part–whole relations) has been represented in well-known conceptual modeling/database textbooks.[1] Figure 1 is part of an entity relationship diagram and presents a "Faculty" entity linked to a "Grad-Student" entity through a "Committee" relationship. In that diagram, the "Committee"[2] is a composite that has a "Faculty" entity and a "Grad-Student" entity as a construct. Figure 2, however, presents an alternate representation, in contrast to figure 1, that demonstrates a composite represented explicitly rather than implicitly. Specifically, a "Committee" is presented as a distinct entity type. This study regards figure 1 as a construct overload model, defined ontological unclear model by Shanks et al. (2008), and figure 2 as a no construct overload model, named ontologically unclear model Shanks et al. (2008). In detail, the Figure 1 "Committee" composite represents implicitly via relationship performing both a composite relationship and a whole part of "Faculty" and "Grad-Student." The figure 2 "Committee" composite represents explicitly via entity. In figure 2, a particular thesis committee can have only one graduate student as a member, and a particular student can be a member of only one committee. Figure 1 presents a single modeling construct (diamond, relationship) that maps to two ontological constructs (relationship of "Faculty" and "Grad-Student" entities and the whole entity). Figure 2 presents a single modeling construct (rectangle, entity) that is mapped to one ontological construct (whole entity). Many studies contend that an implicit representation of composites is more difficult to understand than an explicit representation of composites. The theory supporting that argument and related studies are described next.

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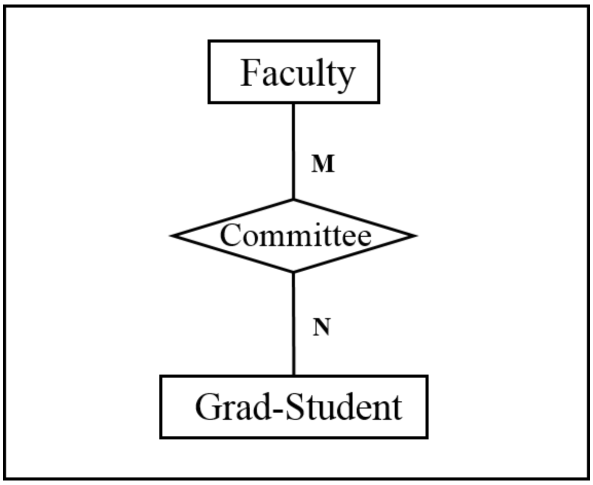
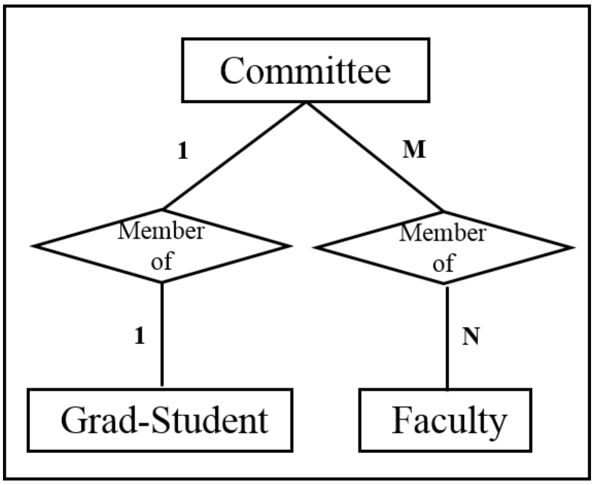
[1] Source: Elmasri and Navathe, Fundamentals of Database Systems, p. 102, Figure 4.9, An EER Schema for a University Database, 2007

[2] Unlike UML (Unified Modeling Language) notation, ER-diagram notation doesn't have the symbol for composite. Composite supports relationships between parts at the same level of decomposition in addition to the usual part-whole relationships.



[Figure 1] "Committee" Composite Represented as an ER Relationship



[Figure 2] "Committee" Composite Represented as an ER Entity

2.1. Theory

The theoretical foundation for our study on conceptual model understanding will be presented in this section. First, we present the theory related to the modeling grammar. The conceptual modeling grammar or rule is used to articulate and communicate a real-world domain, and thus determines results of the modeling process. Therefore, understanding the modeling capabilities and limits of modeling grammar is important for both stakeholder and end users (Recker et al., 2011). Second, we present the theory regarding the interaction between semantics, ontological clarity, and pragmatics, domain knowledge. This theory accounts for how does users' prior knowledge of the domain influences the effect of ontological clarity on the domain understanding. Third, we present the theory about visual attention and protocol analysis indicators cognitive process of users. It explains the reason of performing cognitive process tracing study to recognize the cognitive behavior patterns of model readers.

Theory of Ontological Clarity

Theory of ontological clarity was developed from the adaption of ontological theory proposed by Bunge (1977). It suggests that ontological clarity is completed only when the mapping between a set of conceptual modeling construct and a set of ontological construct is isomorphic. (Wand and Weber, 1993; Shanks et al., 2008). In detail, the theory proclaims that when the constructs of conceptual grammar construct exist in bijective correspondence (one-to-one mapping) with the constructs of an ontology, models developed with that grammar will more effectively communicate meaning to user than models designed to use the grammar with ontological mappings that are either surjective or injective (Wand and Weber, 1993; Suh and Park, 2017). Based on this argument, the theory identifies four situations of undermining a user's ability to understand conceptual model stemming from a lack of isomorphism in the mapping between a set of conceptual modeling construct and a set of ontological construct (Recker et al 2011).

- *Construct overload: A single modeling construct maps to two or more ontological constructs.*
- *Construct redundancy: Two or more modeling constructs map to a single ontological construct.*
- *Construct deficit: An ontological construct exists that has no mapping from any modeling construct.*
- *Construct excess: A modeling construct does not map onto any ontological construct.*

Feynman-Tufte Principle

Feynman-Tufte Principle for simple design and intense content, which is the best way for presentation of data, proposed by Shermer (2005) and Edward Tufte (2006). The principle has the following goals: content focus, comparison rather than mere description, integrity, high resolution, utilization of classic designs and concepts proven by time (Tufte, 2006). Among them, the most important goal he emphasized is content focus. The principle presents the way to focus on content (semantic) efficiently only by data presentation (syntax). He mentioned that to stress semantic, symbol (syntax) must eliminate unnecessary complexity indicating using simple and straight-forward figures with a richness of data (Tufte & Weise, 1997; Tufte, 2006). The basis assumption of design simplicity is the number of figures indicating that the simpler design means a less number of figures (Tufte & Weise, 1997; Tufte, 2006). As a result, a simple figure is more effective than a complex figure when delivering same intense content, semantics. Applying this principle to the conceptual model, if two different conceptual models hope to deliver same semantics to user, the simple design model will be better to offer the meaning.

Mayer's Cognitive Theory of Multimedia Learning

This theory contends that "people learn more deeply from words and pictures than from words alone" (Mayer, 2009 p. 47), and a crucial hypothesis underlying the research of multimedia learning is that multimedia instructional messages designed based on the way of human mind works are more likely to lead to meaningful learning than those that are not (Mayer, 2001; Suh and Part, 2017). The assumption is that humans involve in active learning by calling upon prior knowledge, applying knowledge in understandable mental representations, and integrating mental representations with knowledge (Suh and Part, 2017). Mayer's cognitive theory of multimedia learning represents a principle regarding how people learn from words. It is based on the idea that human possess separate channels for processing verbal material, and each channel can process only a small amount of material at a time. Meaningful learning involves engaging in appropriate cognitive processing during learning (Mayer, 2001). In other words, readers cannot but understand the models considering their prior domain knowledge. When humans internalize a conceptual model, they do not internalize it "as is," but, rather, tend to internalize it in a manner that is suitable to their existing mental model of that domain in long-term memory (Ashcraft, 2002; Bera et al. 2014; Chinn and Brewer, 1993; Suh and Park, 2017).

Information Processing Theory

Newell and Simon's (1972) information processing theory offers a conceptual foundation for the application of protocol analysis. According to theory, complicate cognitive behavior is compounded out of consecutive of elementary information processes (Newell and Simon, 1972; Ericsson and Simon 1993). In detail, each of these sequences states can be explained in terms of chunks, the small number of information structures that are available in the limited-capacity short-term memory store. Although information processes may also access information from the vast permanent memory or long-term memory store, but the result of such access processes will be to make the information available in short-term memory store. Within this theoretical context, the basic assumption that underlies the understanding of verbal protocols is that only information that is heeded, in consequence of being brought into short-term memory by the continuing cognitive processes, can be processed further and verbalized directly. The assumption gives significant implications for (1) the kinds of instructions to participants that will present verbalizations revelatory of their cognitive processes, and (2) the kinds of methods that are effective for analyzing and interpreting the recorded verbalizations (Ericsson and Simon, 1993).

Theory of Visual Attention

Bundesen (1990)'s theory of visual attention (TVA) provides that visual recognition and attentional selection consist in making perceptual categorizations. A perceptual categorization has the form "*x* belongs to *i*; where *x* is an element in the visual field and *i* is a perceptual category. Example of perceptual category is red belongs to a color category. (Bundesen, 1990). The basic assumption of TVA is that visual attention, in its most fundamental sense, is a selective visual process that governs access to consciousness. In other words, the eye-tracking, a measure of visual attention, is a significant clue in understanding the user's cognitive behavior because the eye provides input for 90% of the information used in human cognitive activity and can serve as an instructional material by providing access to perceptual (Bundesen, 1990, Levelt et al. 1999, Gog and Scheiter, 2010).

2.2. Related Work

Table 1 provides a brief summary of previous research related to the conceptual model. Among them, we would like to examine deeply the study regarding the ontological clarity provided by Wand and

Weber (1993) and domain familiarity related to the research that we plan to conduct.

Author	Title	Subject	Model	Task	Result
Lochovsky and Tsichritzis (1977)	User performance considerations in DBMS selection	Less experience vs. More experience	Relational Network	Query Writing	
Brosey and Shneiderman (1978)	Two experimental comparisons of relational and hierarchical database models	Beginner vs. Advance	Relational Hierarchical	Comprehension , Problem Solving, Memorization	Advance is better
Batra et al. (1990)	Comparing representations with relational and EER models	42 Students	Relation Model vs. Extended Entity Relationship	User Performance in Modeling and Specifying Identifiers of the Respective Entities, Ease of use	EER is better
Kim and March (1995)	Comparing Data Modeling formalism	28 Graduate Business Students	EER vs. NIAM	Syntactic and Semantic Performance	Syntactic Performance is similar/ EER is better in Semantic Performance
Shoval and Shiran (1997)	Comparing Entity-relationship and object-oriented data modelling	44 Students majoring Information Systems	Entity Relationship Diagram(ERD) vs. Object-Oriented Model	Comparing Design Quality, Correctness, Time, Designers' Preference	ERD is better
Agarwal et al. (1999)	Comprehending Object and Process Models: An empirical study	71 Undergraduate Students majoring MIS	Object Diagram vs. Data Flow Diagram	Accuracy of Comprehension	Similar but in case of complex question Process Model is better
Bodart (2001)	Should optional properties be used in conceptual modelling?	52 Students majoring Computer Science	ERD (Optional Property)	Free Recall, Comprehension , Problem Solving	In case of surface level Optional Properties are needed, but Optional Properties should not be used when user requires deep understanding
Shanks et al. (2003)	Representing things and properties in conceptual modelling: an	33 Individuals (Non-expert)	Entity only ERD, Practice ERD, Ontologically Sound ERD	Comprehension and Problem Solving	Ontologically sound representation significantly improved

	empirical evaluation				comprehension performance but had no significant effect on problem-solving performance.
Corral et al. (2006)	The impact of alternative diagrams on the accuracy or recall: A comparison of star-schema diagram and entity-relationship diagram	109 MISM students and 41 MBA students	Star-Schema vs. ERD	Accuracy and Pattern of Users' Recall	Star-schema is better
Allen and March (2006)	The effects of state-based and event-based data representation on user performance in query formulation tasks	342 Subjects from 6 Universities conducted over Internet	State-based vs. Event-based ERD	Actual Query Accurance, Level of Confidence expressed	No difference
Khatri et al. (2006)	Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge	81 Undergraduate Business Students	ERD (Sales Schema vs. Hydrology Schema)	Schema Understanding Task ,Comprehension Task	IS domain knowledge is important in the solution of all types of conceptual schema understanding tasks in both familiar and unfamiliar applications domains
Shanks et al. (2008)	Representing part-whole relations in conceptual modeling: an empirical evaluation	30 Individuals working in industry who had little, if any, experience of conceptual modeling (Non-Expert)	Ontologically Clear UML Class Diagram vs. Ontologically Unclear UML Class Diagram	Comprehension and Knowledge Identification	Ontologically Clear UML Class Diagram is better
Recker et al. (2011)	Do ontological deficiencies in modeling grammars matter?	528 Modeling Practitioners	BPMN (Business Process Modeling Notation)	Comprehension	Users of conceptual modeling grammars perceive ontological deficiencies to

					exist, and that these deficiency perceptions are negatively associated with usefulness and ease of use
Bera et al. (2011)	Guidelines for designing visual ontologies to support knowledge identification	22 Student taking the Introduction to MIS and Accounting Information Systems/100 Students	Guided Ontologies vs. Unguided Ontologies	Comprehension and Knowledge Identification	Guided Ontologies is better
Allen and March (2012)	A Research Note on Representing Part-Whole Relations in Conceptual Modeling	University Students who had received several months training on UML => Trained Student	Ontologically Clear UML Diagram vs. Ontologically Unclear UML Diagram/Three Binary Relationship vs. Ternary Relationship Model	Comprehension and Problem Solving	Ontologically Unclear UML Diagram is better/Three Binary Relationship Model is better
Bera et al. (2014)	Research Note: How Semantics and Pragmatics Interact in Understanding Conceptual Models	54 students from university in the U.S. taking MBA courses in management information systems and DB	EER Models (Library, Aquarium Management, Pharmacology).	Guided scripts versus unguided scripts on participants' performance in problem solving questions	Benefit of ontological clarity on understanding is concave downward (follows an inverted-U) as a function of readers' prior domain knowledge. The benefit is greatest when readers have moderate knowledge of the domain shown in the model.
Clarke et al. (2016)	On the Ontological Quality and Logical Quality of Conceptual-Modeling Grammars: The Need for a Dual Perspective			Provides a new perspective on ways to improve the quality of the semantics of Conceptual Modeling grammars.	

Suh and Park (2017)	Effects of Domain Familiarity on Conceptual Modeling Performance	60 students from university in the Korea taking Database courses	Ontologically Clear ERD vs. Ontologically Unclear ERD	Comprehension and Problem Solving	No difference

[Table 1] Previous Empirical Research on Data Modeling

Ontological Clarity

Recker et al. (2010) found that construct deficit make users apply additional means to articulate the real-world phenomena. Bodart et al. (2001) and Gemino and Wand (2005) presented how the existence of construct excess in a conceptual model resulted in users misunderstanding the model. Construct overload, however, still showed the controversial results. As previously mentioned, Shanks et al. (2008) claimed that construct overload undermined users' ability to understand the information contained in the model. It means that an ontologically clear model (i.e., no construct-overloaded model) enables users to better recognize a domain, indicating that a distinction between an entity and a relationship is needed. In contrast, Allen and March (2012) questioned the argument by Shanks et al. (2008), conducted two experiments that both address construct overload issue and proposed a contrary conclusion, and described the theoretical underpinning for the study by Shanks et al. (2008).

Domain Familiarity

The concept of domain familiarity refers to people's level of existing knowledge about a given topic or domain (Glenberg and Epstein, 1987; Shanks and Serra, 2014, Suh and Park 2017). If a person is familiar with a certain domain, he or she has a high level of knowledge about that domain. Therefore, people's domain familiarity is predictive of performance on tasks related to the topic(s) about which they possess either high or low knowledge levels (Feltovich et al., 2006; Shanks and Serra, 2014). Burton-Jones and Weber (1999) studied the effects of the interrelationship of domain knowledge and different ways of representing relationships with attributes, referred to as ontologically sound and unsound representations, on understanding a conceptual model. They found that while performance with each representation was similar when domain knowledge was present, performance with the ontologically sound representation was better than the unsound representation when domain knowledge was not present. Siau et al. (1995) conducted an experiment to understand how experts used structural constraints (cardinality) associated with binary relationships in familiar and unfamiliar domains. They found no differences in comprehension of structural constraints in the two domains. Khatri et al. (2006) studied the effects of IS and application domain knowledge[3] on conceptual schema understanding by using problem solvers with high and low IS knowledge in both familiar and unfamiliar application domains. They found no interaction between IS and application domain knowledge; IS domain knowledge influenced the solution of all forms of conceptual schema understanding, an application domain knowledge did not influence the solution of comprehension tasks. Bera et al. (2014) studied the significance of clear semantics in conceptual models, depending on the pragmatics of readers' domain knowledge presented in the script. They demonstrated that the benefit of ontological clarity in understanding is concave downward as a function of domain knowledge. When readers possess moderate domain knowledge, they receive the greatest benefit. In detail, they selected the manipulated ontological clarity via construct overload by using the extended entity-relationship (EER) model and regarded a model distinguishing between things and roles in a domain as a guided script and a model violating the distinction between things and roles in a domain as an unguided script. This research also selects ontological clarity via construct overload, but our study focuses on explicit or implicit expression of a relationship indicating that several ontological constructs, composite entity and relationship, are mapped within each modeling construct, part-whole relation or distinct entity.

3. Proposition Development

Theory of ontological clarity argue that when a single modeling construct is used to represent two ontological constructs, *construct overload* arises, resulting user of conceptual model will have difficult to

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[3] Domain knowledge is knowledge of the area that contains all forms of knowledge, including both procedural and declarative aspects (Alexander 1992, Bera et al., 2014).

comprehend the semantics of real-world domain represented by the model. Some studies have empirically tested this argument. Shanks et al (2008), for instance, demonstrated that construct overload undermines user's ability to understand the information contained in the model, Allen and March (2012), however, question the argument and propose the opposite conclusion. In addition, Date (2003, p. 436) eschews the distinction between an entity (thing) and a relationship (type of property of a thing): "In this writer's opinion, any approach that insists on making such a distinction is seriously flawed, because… the very same object can quite legitimately be regarded as an entity by some users and a relationship by others" (cited in Shanks et al. 2010).

Wand and Weber's (1993) theory of ontological clarity, are rooted in computational and algorithmic theories rather than neurophysiological theories of human visual object recognition systems (Biederman 1987; Bruce et al. 2003; Shanks et al 2008). Nonetheless, Marr's (1982) seminal study presents that computational and algorithmic theories have priority over neurophysiological theories. As a computational and algorithmic theory, the theory of ontological clarity supports a rationale for why ontological clarity is significant (Shanks et al., 2008). The theory does not account for neurophysiological processes, however, to support why this outcome will occur.

In addition, in conceptual modeling research, the majority of laboratory experiments used student subjects. Table 2 shows the distribution of studies in terms of research methodology based on data about the nature and extent of the use of student subjects in Information Systems Research (ISR) and MIS Quarterly (MISQ) over the last 20 years, 1990-2010. In terms of methodology, the vast majority of the studies using student subjects were laboratory experiments (76.3%) and most of conceptual modeling research used the laboratory experiments (Compeau et al., 2012). In other words, most laboratory experiments in conceptual modeling studies use students as subjects.

Research context based on Vessey et al. (2002) categories	Information Systems Research		MIS Quarterly		Total	
Methodology	Count	Percent (%)	Count	Percent (%)	Count	Percent (%)

Lab experiment	70	82.4	46	68.7	116	76.3
Survey	13	15.3	19	28.4	32	21.1
Other (case study, mixed methods)	2	2.4	2	3.0	4	2.6

[Table 2] Research Methodologies for Studies Using Student Samples[4]

The use of students as research subjects, however, has been disputed along with the discussion of generalizability because of the low external validity. Sears (1986) contended that, "college students are likely to have less crystallized attitudes, less- formulated senses of self, stronger cognitive skills, stronger tendencies to comply with authority, and more unstable peer group relationships" (p. 515). He further claimed that these differences may lead to flawed conclusions (cited in Compeau 2012). Schultz (1969) argued that students are more likely to answer questions dishonestly, either to try to deceive the researcher or to give "good" or supportive data. Tolman (1959) expressed the most extreme view of this: "college sophomores are apparently not real people" (p. 7). Davis et al. (2005) stated that it is hard to assert that the major user of conceptual modeling is the student, even if he or she learned some courses related to Information Systems, because the practitioners who still embraced conceptual modeling, such as (a) building a conceptual model, (b) supporting communication tools between developers and users, (c) assisting analysts to recognize a domain, and (d) offering input for the design procedure could be the actual user of the conceptual model (Batra et al. 1990; Kung and Solvberg 1986; Wand and Weber 2002). In addition, a few studies have examined the problem-solving processes employed by practitioners. Studying practitioner's performance regarding construct overload can contribute to a deeper understanding of what the expert (Larkin et al. 1980; Chi, Glaser and Farr 1988; Batran and Davis 1992).

The construct overload issue still remains unsolved. Furthermore, the potential performance difference between the research subjects in the conceptual modeling studies, i.e., students vs. actual users who use the conceptual models in their businesses (we call them practitioners), may lead to a contradictory conclusion. Therefore, we present the following proposition.

4 Source: Compeau et al., Generalizability of IS Research Using Student Subjects, Information Systems Research, 23(4), pp. 1096, Table 2

Proposition 1*: Construct overload is a salient predictor of practitioners' performance* (in other words, *construct overload affects actual user performance.*)

Mayer's Cognitive Theory of Multimedia Learning proves that users cannot help interpreting the scripts in light of their prior domain knowledge; in other words, when humans internalize a script, they do not internalize it as presented, but rather tend to internalize it in a way that fits their existing mental model of that domain in long-term memory (Ashcraft, 2002; Bera et al., 2014; Chinn and Brewer, 1993; Suh and Park, 2017). Domain knowledge, essential to all disciplines (Alexander 1992), is the knowledge of the area to which a set of theoretical concepts is applied (Khatri et al. 2006). It has long been recognized as an important study being conducted in such diverse areas as physics, economics, and history. Such studies have discovered that thinking is dominated by content and skills that are domain specific (McPeck 1990) and that less-efficient problem-solving strategies result from the lack of domain knowledge (Alexander and Judy 1988).

The term "domain knowledge" has a dual meaning in the information systems (IS) discipline. One refers to the IS domain knowledge which is needed to form the basis for the development of application systems such as knowledge about representations, methods, techniques, and tools. The other is application domain knowledge, which is required to organize or structure solutions to real-world problems (Khatri et al. 2006). Therefore, IS and application domains knowledge should cooperate to solve IS problems. Some research has examined the processing aspects of domain knowledge, but far fewer studies emphasize data aspects such as conceptual modeling (Vessey 2006) and the domain knowledge of conceptual modeling users (Suh and Park, 2017). Even if they have, most studies have performed within familiar domains such as the library domain for university students (Bera et al. 2014), the project-planning domain for industry workers (Shanks et al 2008), and the business domain, Collaborative Auditing Incorporated (CAI), for university students majoring in MIS (March and Allen 2012). In familiar domains, construct overload in models could be accepted and interpreted, because users can apply past knowledge to resolve the overload and suppose that the domain operates as they expected. In other words, familiarity bias arises (Hadar et al. 2012). Generally speaking, the results of the existing studies on construct overload performed in familiar domains may not accurately measure performance due to the users' high domain knowledge. For a more accurate research outcome, a conceptual modeling study must be conducted with unfamiliar domains in which domain knowledge is less influenced. If the construct-overloaded model with unfamiliar domains is interpreted precisely, it will be difficult to say that construct overload is a problematic issue in the conceptual modeling practice in the real word, because research suggests that it is hard to apply one's domain knowledge to unfamiliar domain (McPeck 1990; Alexander and Judy 1988). Therefore, we present the following proposition.

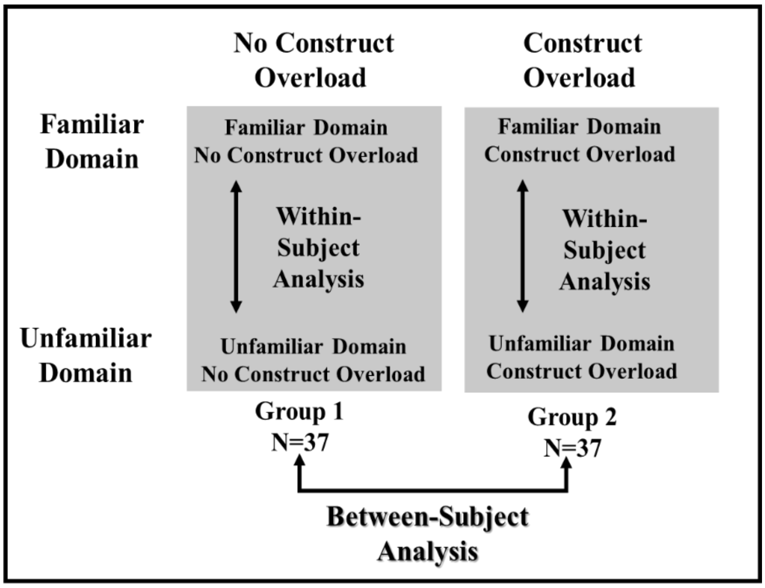
Proposition 2*: *A construct overload in an unfamiliar domain will make it difficult for users to understand the model properly. Or A familiar domain model can help users understand the model properly even if it contains overloaded constructs.

4. Research Method

A laboratory experiment was employed to (a) control for extraneous factors that might confound any impacts of alternative representation of construct overloads on how well users understand conceptual models regarding the existence or nonexistence of construct overload, (b) attain support for a cause-effect relationship between existence of construct overload and user performance that we represented in a conceptual model, and (c) acquire sufficient numbers of participants in our research to statistically test our hypotheses.

4.1. Design and Measures

The experiment used a mixed within-and-between design, with construct overload manipulated between groups and domain familiarity manipulated within groups. As a result, each participant received either the construct overload models (i.e., ontologically unclear models) or the no construct overload models ontologically clear models (i.e., ontologically clear models) by random assignment reducing the learning effect and also received the questionnaire for both domains, familiar and unfamiliar. The complete experimental design is summarized in Figure 3.



[Figure 3] Experimental Design

Determining a dependent variable is critical factor of the conceptual model, because in practice, users of a conceptual model might understand semantics from a diagram in consultation with others and the result of such contact is difficult to elicit the precise semantics of the model given to the users. To correctly measure how well the conceptual model delivered semantics to users, and at the same time to eliminate as many confounding features as possible in evaluating this outcome, prior research selected Mayer's (1989) measures of performance based on recall, comprehension, and problem-solving as dependent variables (e.g., Bodart et al., 2001; Gemino and Wand, 2005; Parsons and Cole, 2005). These tasks act as a proxy for how well users educe semantics from the conceptual model in practice (Shanks et al., 2008; Suh and Park 2017).

In this research, problem-solving performance is used as the dependent variable, because compared to recall and comprehension performance, problem-solving performance offers a better indicator of a user's deep understanding of a domain (e.g., Bloom, 1956; Shanks, 2008; Suh and Park 2017). To measure problem-solving performance, problem-solving accuracy is selected. It was evaluated in terms of whether participants acquired a correct answer to the problem and expressed as the percentage of problem-solving questions correctly answer by each participant (Shanks et al., 2010). The study also uses an additional measure of performance: problem-solving time taken to provide a problem's answer and expressed in minutes. If the conceptual model better conveys domain semantics to participants, then participants will solve problems faster. (Suh and Park 2017).

4.2. Materials

Four sets of materials were developed for the experiments. This study presents them below in three subsections: personal profile and training materials, conceptual models and understanding task materials.

Personal Profile and Training Materials

Two sets of materials were used in the experiments. The first set of materials comprised a personal profile questionnaire to acquire information about participants' academic qualifications, the industry in which they worked, the number of years they have spent in the database field, the number of years they have spent in modeling, the most frequently used conceptual modeling techniques and tools, and the most significant objective of using conceptual modeling. These materials were used to determine whether the participants who received the different treatments had similar educational level, qualifications, and experience, etc.

The second set of materials was a summary of the ER diagram symbols that were presented in the diagrams. This was prepared to inform participants of the meaning and usage of each ER diagram symbol. In the materials provided to participants, whether they were to receive the construct overload model or not, the meaning of a ternary relationship was explained, and an example was presented. Note that to increase our contribution to conceptual modeling practice, we decided to base our study on the ER approach to conceptual modeling, because this approach has been generally used in practice (Rosemann et al., 2003; Simsion and Witt, 2001; Suh and Park 2017). Additionally, we performed a preliminary interview with several practitioners to decide which conceptual modeling technique to use for the script. More than 90% of practitioners answered that they learned and used the ER diagram as a conceptual modeling technique.

Conceptual Models

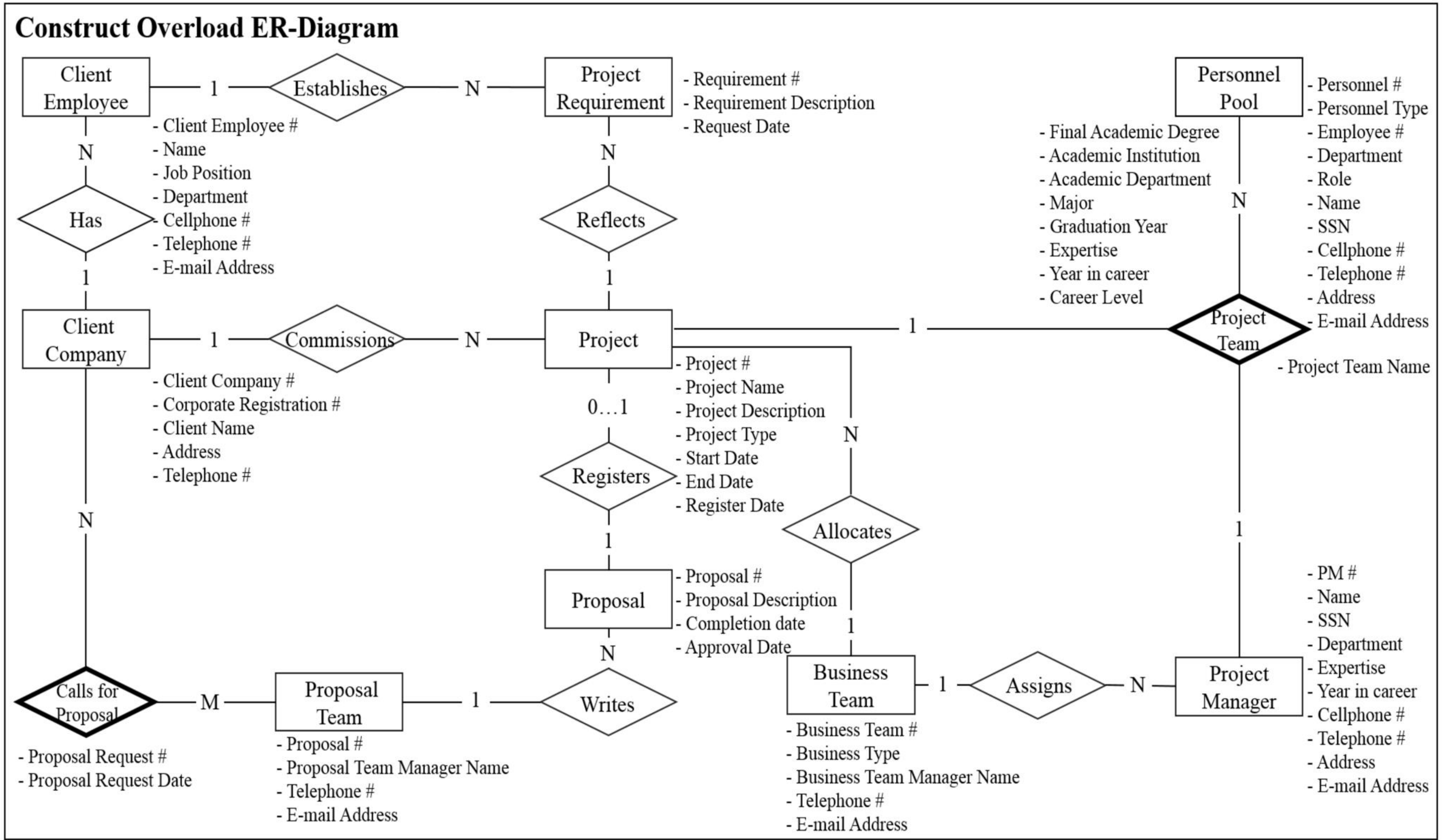
The third set of materials consisted of four ER diagrams of a familiar domain (project management system) and an unfamiliar domain (waste processing system), and each domain had construct overload and no construct overload diagrams. The pilot study was performed with practitioners who were database and modeling experts with respect to domain selection. First, they reviewed the model domain list that had been submitted to the Korean DA Design Contest from 2005 to 2014 and scored the numbers in their model familiarity order (1 for the most familiar model and 10 for the least familiar model). The most familiar model domain was a project management system, while the least familiar model domain was a waste processing system, which resulted in the selection of these two as the conceptual model domains. Each domain consisted of the models with and without construct overload.

Figures 4, 5, 6, and 7 present familiar and unfamiliar domain diagrams. Figures 4 and 6 show a construct overload model in each domain. In other words, both the ontological construct (composite) entity and the relationship were represented as only one grammatical construct, relationship (diamond symbol). Figures 5 and 7 present a no construct overload model in each domain. In other words, the (composite) entity is represented as a distinct entity, and the relationship between the two entities is presented as a relationship. For example, in Figure 4, the “Project Team” construct shown as a ternary relationship is used to present two ontological constructs, the part-whole relationship of “Personnel Pool,” “Project Management,” and “Project,” and composite entity, the whole part of “Personnel Pool,” “Project

Management," and "Project." Additionally, the "Calls for Proposal" construct shown as a relationship is used to present both of the relationship between "Client Company" and "Proposal Team" and entity. However, in Figure 5, the "Project Team" construct presented as a separate entity is used to present the composite entity; and "Calls for Proposal" construct presented as a discrete entity is used to present the entity on the no construct overload ER diagram.

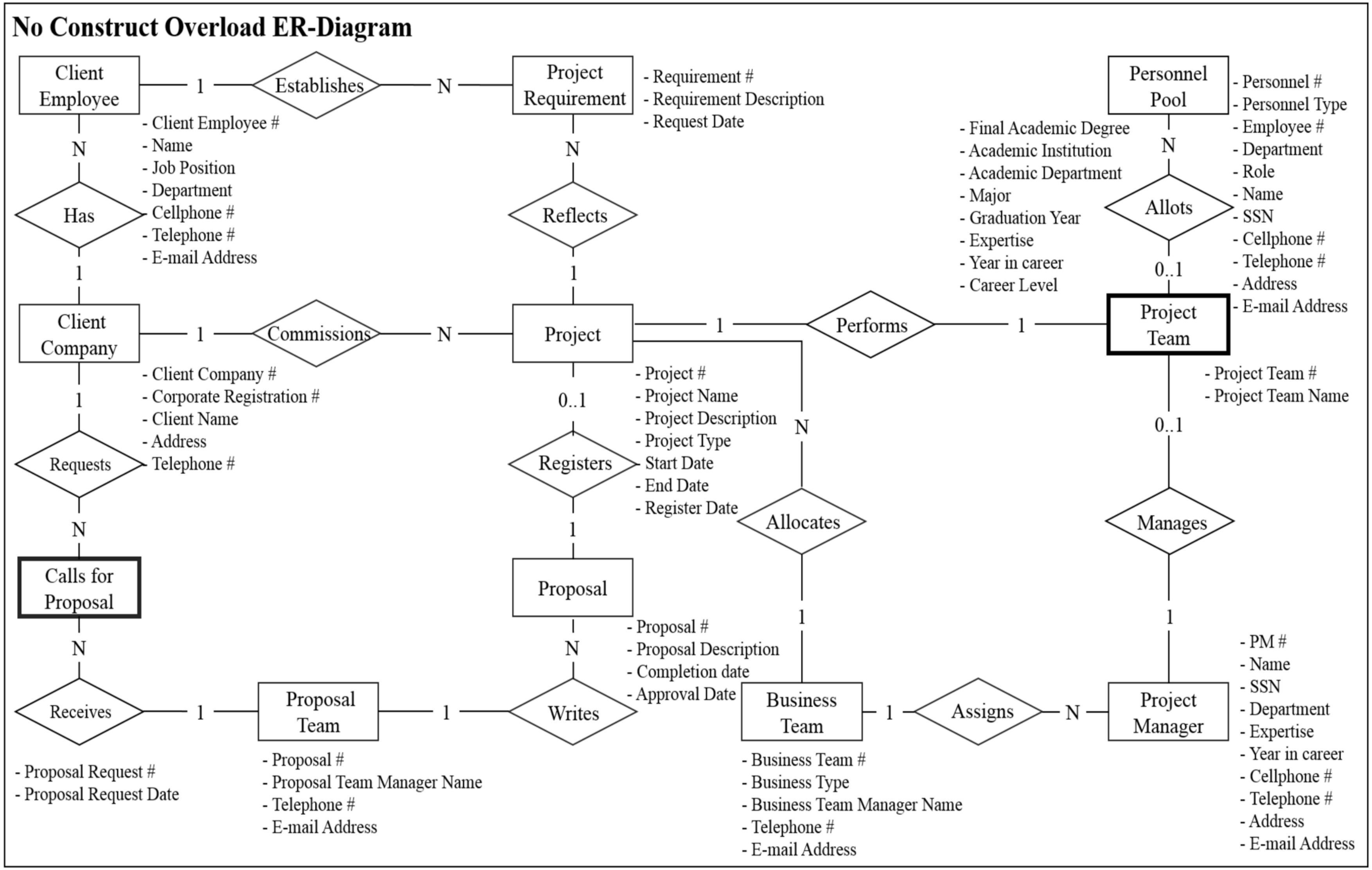
Allen and March (2012) study argue that the semantics of ternary relationships are significantly more difficult to comprehend than are the semantics of binary relationships, especially for novice users (Topi and Ramesh 2002; Allen and March 2012). Inclusion of ternary relationships in the construct overload model treatment but not in the no construct overload treatment represents a significant confound, making it impossible to determine the source of observed performance differences. In our research, however, participants were not novice users but practitioners, expert in modeling technique, therefore using ternary relationship in the model does not give them an intentional comprehension difficulty when they read the model. Also, unlike Unified Modeling Language (UML), the conceptual modeling technique that Shanks et al (2008) and Allen and March (2012) used to their experiments, there is no notation to represent the composite entity in ERD, so representing a composite as a relationship or entity is the fundamental point that underlies our experiment and use of ternary relationship is not a confound, it is the essence of treatment.

Some argument can be raised the use of not a 'thing' like call-for-proposal, the event in our model. Shanks, Tansley, Nuredini, Tobin and Weber (2008), however, used an event "Purchase Requisition" in their class diagram when they performed the experiment. In detail, "Purchase Requisition" is represented as a relationship in the ontologically unclear diagram (construct overload) and entity in the ontologically clear diagram (no construct overload diagram). In addition, Bunge's ontology (p.119), theoretical foundation of theory of ontological clarity, mentioned that "theoretical science and ontology handle not concrete things but *concepts of such* [our emphasis], in particular conceptual schemata sometimes called model things. Our construal of a thing as a substantial individual together with the set of all its properties…is of course such a model thing." Therefore, we use concept like process, contract, and transport as a “thing”.

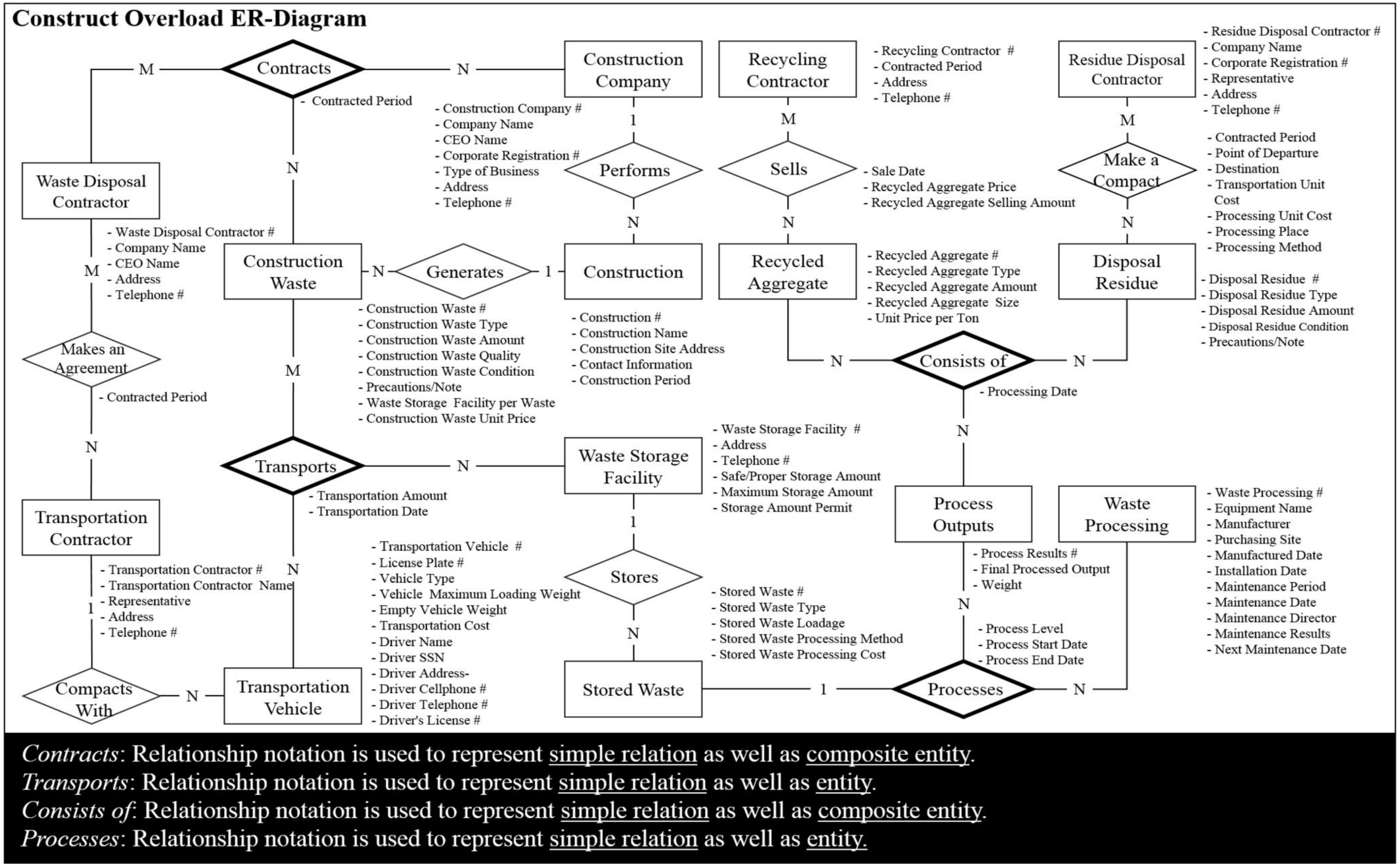


Calls for Proposal: Relationship notation is used to represent simple relation as well as entity.
Project Team: Relationship notation is used to represent simple relation as well as composite entity.

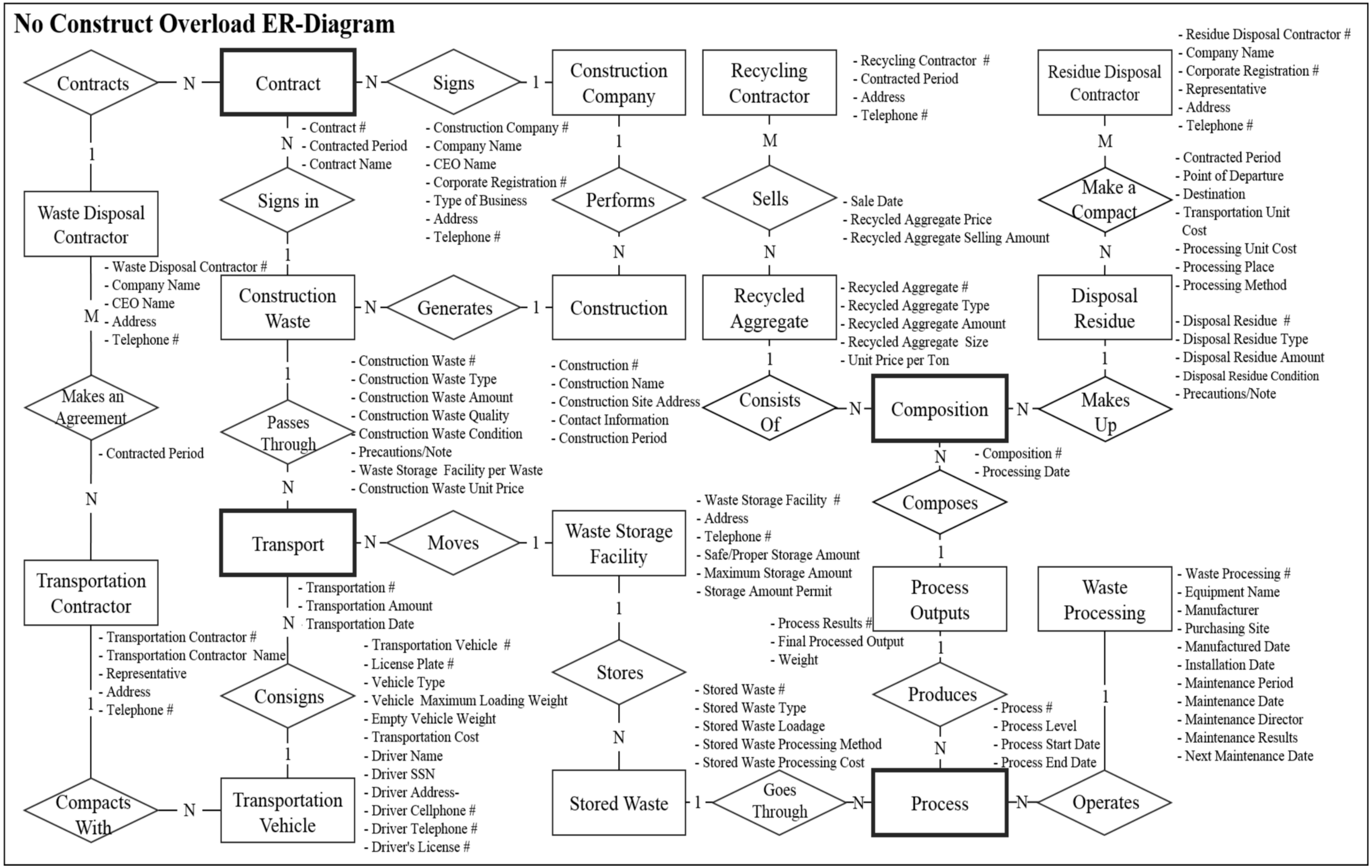
[Figure 4] Construct Overload Model in Familiar Domain (Project Management System) ER-Diagram



[Figure 5] No Construct Overload Model in Familiar Domain (Project Management System) ER-Diagram



[Figure 6] Construct Overload Model in Unfamiliar Domain (Waste Processing System) ER-Diagram



[Figure 7] No Construct Overload Model in Unfamiliar Domain (Waste Processing System) ER-Diagram

Understanding Task Materials

The fourth set of materials consists of 12 problem-solving questions of each familiar and unfamiliar domain to which participants should provide a response of "yes" or "no." Figure 8 and 9 provide the questionnaires of the familiar domain and unfamiliar domain. To increase the reliability of the study, we used the same questionnaires in Suh and Park 2017. The questions were the outcome of a review of existing studies and extensive discussions among management information systems professors, database administrators and practitioners. They were designed to (1) deliver strong coverage of the different semantics represented in the ER diagrams, (2) represent different levels of complexity, (3) confirm equal levels of difficulty in both domains, and (4) induce participants use the ER diagrams to answer correctly rather than depending upon their domain knowledge. Eight of 12 questions were designed to force participants to focus on semantics, which are directly related to the construct overload issue. Some questions such as questions 6 and 11 in the familiar domain questionnaire and questions 4 and 11 in the unfamiliar domain questionnaire were regarded as baseline questions and were chose to guarantee that any performance differences between two groups would be attributed to the experimental treatment rather than other confounding factors.

Question
1. A client company verbally promises to commission a new project. The client company requests the proposal team for a proposal and the business team assigns a project manager (PM) suitable to that field. Although specific project requirements are not established, a project team is planned to be organized. Can you organize a project team before the project requirements are determined?
2. Can personnel selected for a project team participate in another project?
3. The client employee requests a new form of work, which is not included in the original requirement list. In this case, can the existing project team perform this project by reflecting the newly added requirement in the list?
4. It has been six months since a client company has commissioned a one-year project. However, the project manager (PM) suddenly resigns. Can this project be conducted without the project manager (PM)?
5. The personnel selected for one project team will be maintained for the duration of the project if possible; however, based on this model, would it be possible to exchange or add personnel during the project lifetime due to several circumstances?

6.	Our company is concerned that those personnel with more career experience than the project manager (PM) may have too much influence on the overall project. Could the company prepare for this situation by making a list of personnel in the personnel pool who have more experience than the project manager (PM)?
7.	It has been three months since the project has commenced after a project team related to the commissioned project was organized. One day, the team members read the proposal and realize that the current requirements do not sufficiently reflect the contents of the proposal. Could the project team members make a list of new requirements that are more aligned with the proposal?
8.	Could it be determined which project manager (PM) is currently not associated with any project team?
9.	While a project is being conducted, another project very similar to the field of the current project is proposed. In this case, would one project manager (PM) be able to manage the similar project at the same time?
10.	Would the project manager (PM) be able to check the project requirements prior to allocation of the project and determine whether he or she is suitable for the project?
11.	A client company has recommended a project manager (PM) suitable to the field of a project related to the requested project. Can the business team record that project manager (PM) before the business team and project manager (PM) have been determined?
12.	A client company has requested a proposal for two similar projects on the same day. The proposal team writes both proposals. However, the client company suddenly requests the proposals to be scaled down to one proposal because the contents of the two projects are similar. Based on this model, would it be possible to write the two proposals into one proposal as requested?

[Figure 8] Familiar Domain (Project Management System) Questionnaire

Question
1. The construction company has requested the scope of the waste-related contract to be scaled down due to financial difficulty. The waste disposal contractor will gladly renegotiate the contract. In this case, can the contract with the transportation contractor be scaled down at the same time?
2. The amount of construction waste was found to differ from the amount of construction waste stored in the waste storage facility. Can the waste disposal contractor responsible for causing this difference be identified?
3. The stored waste was processed to generate recycled aggregate and disposal residue. Would it be possible to calculate the profit and loss of the waste disposal process?
4. The construction company would prefer to immediately incinerate the harmful construction waste without processing it. In this case, could the transportation contractor send the waste directly to the residue disposal contractor?
5. The construction waste that was temporarily stored in the waste storage facility was known to exceed the allowed storage limit of the jurisdictional district. At this time, could the contractor who was in charge of the transportation be held responsible?
6. All of the stored waste has become disposal residue that cannot be sold due to an error in the waste processing system. Could the person in charge of waste storage be held responsible for this?
7. The process outputs are reported in writing once a month. Can the written report be used to check whether there is difference between the weight of the final processed output and the total amount of the recycled aggregate and disposal residue?
8. The dates on which processing started and ended are the same and the raw materials (stored waste) are the same, but the final outputs are different. In this case, can it be determined whether this difference is due to problems with the equipment?
9. When the different types of stored waste pass two-step processing, they become the same final processed output. However, these equivalent outputs were sold as different types of recycled aggregate. Would it be possible to determine whether this error occurred because of the processing procedure?
10. Of two tons of equivalent recycled aggregate (aggregate # is the same) that were sold on the same date, one ton passed two-step processing and one ton passed four-step processing. Can it be determined whether different processes were used because of different types of construction waste?
11. It has been six months since the construction company and the waste disposal contractor signed

	a one-year contract. However, the contracted waste disposal company suddenly shuts down this month. In this case, can the construction waste that is currently being processed successfully complete the processing for part of the products to be sold as recycled aggregate and the remaining disposal residue be reclaimed and incinerated?
12.	One transportation vehicle driver is allocated to drive at least 10 times a week. However, two transportation vehicle drivers split the driving duty because of inevitable conditions. Would the waste disposal contractor be aware of this situation?

[Figure 9] Unfamiliar Domain (Waste Processing System) Questionnaire

4.3. Participants

The total participants in the experiment were seventy four practitioners working in various industries and willing to help us with the experiment. Among them, forty eight participants were took part in quantitative analysis and the remainder, twenty six participants, joined in cognitive process tracing research which will be explained in the next section. Because of the concerns regarding student participants (Compeau et al. 2012) mentioned earlier, we selected the modeling experts as research participants. All of quantitative analysis participants have at least a five-year database career as a database manager and/or administrator. Davis et al. (2005) presented the top six most commonly used modeling techniques stratified according to the years of modeling experience of the practitioners and the results presented that a significant increase in usage from the 0-3 years level to the 4-10 years level of experience. Accordingly, we selected participants who fit the above category. All participants acted as surrogate application system stakeholders in the experiment, because they: (a) generate a conceptual model, (b) communicate with developers and end users, and (c) assist analysts to recognize a domain. Table 3 presents demographic data about all the seventy four participants. All of them have a technical information system role in their organization and had at least a bachelor’s degree.

Industry Sector	Familiar Domain Project Management System	Unfamiliar Domain Waste Processing System	Total
Electrical and Communication	4	5	9
Entertainment (Game, Music)	20	22	42
Distribution Industry	1	0	1
IT/IT Consulting	8	5	13
Public Sector	2	3	5
Etc.	2	2	4
Time in Database Field	**Familiar Domain Project Management System**	**Unfamiliar Domain Waste Processing System**	**Total**
1-5 Year	8	6	14
6-10 Year	26	28	54
11-15 Year	3	3	6
Time in Database Field	**Familiar Domain Project Management System**	**Unfamiliar Domain Waste Processing System**	**Total**
1-5 Year	16	15	31
6-10 Year	20	22	42
11-15 Year	1	0	1

[Table 3] Participant Demographic Data

4.4. Procedures

Forty eight participants were first randomly assigned to one of the two treatments (24 per treatment) related to the existence of construct overload. Then, the experiment performed through two phase: training and main study. In the *training* phase, the task participants were to perform and the nature of the experiments were explained to them. Then, they were then given the document that explained the ER diagram symbols. If they had questions about symbols and examples, their questions were answered. This procedure continued until they felt confident about the ER diagrams. Participants were able to refer to the ER diagram symbol documents during the experiment. When participants suggested that they were ready to start, the next phase, the *main study*, begun. First, participants were given a consent form and a questionnaire to acquire demographic and experiential information then they were given either construct overload or no construct overload ER diagrams that reflected both familiar and unfamiliar domains. The order of domain familiarity was randomly given. Participants undertook the problem-solving tasks, and the time they took to answer each problem-solving question was recorded. On average, it took about 57 minutes to complete both the familiar and unfamiliar questionnaires.

4.5. Results

The results were analyzed at three phases. First, scores for individual items on the problem-solving measure were calculated. Second, the hypotheses was tested by performing statistical analysis to understand treatment differences in the scores for the problem-solving and time.

Data Scoring

Scores were awarded as follows. One mark was given if the answer (“yes” or “no”) was correct; zero was given if a participants’ answer was incorrect or left blank. Participants were encouraged not to answer the question by guessing. Twoe participant’s answer sheet had one blank answer and one answer sheet had three blank answers.

Quantitative Data Analysis

Table 4 presents descriptive statistics for dependent measures in familiar domain. We undertook one way ANOVA test to know the difference between groups, construct overload and no construct overload model in each familiar and unfamiliar domain. Controlling the effect of unfamiliar domain, we compare the comprehension accuracy, total score, of construct and no construct model in familiar domain. As shown in table 5, for comprehension accuracy, the difference between the two groups, construct overload and no construct overload, was not statistically significant using ANOVA test ($F = 0.000$, sig = 0.996, $p = 0.1$)

Familiar Domain Construct-Overload vs. No Construct Overload	Mean	Std. Deviation	N
Construct-Overload	8.95	1.810	37
No Construct-Overload	8.95	1.870	37
Total	8.95	1.827	74

[Table 4] Descriptive Statistics for Dependent Measures: Familiar Domain

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.060a	2	.530	.155	.857
Intercept	248.132	1	248.132	72.582	.000
Covariate (Unfamiliar Domain Construct Overload Vs. No Construct Overload)	1.060	1	1.060	.310	.579
Familiar Domain Construct Overload Vs. No Construct Overload	.000	1	.000	.000	.996
Error	242.724	71	3.419		
Total	6166.000	74			
Corrected Total	243.784	73			

a. R Squared = .004 (Adjusted R Squared = -.024) ※ *p<0.1, **p<0.05, ***p<0.01

[Table 5] Accuracy Performance between Construct Overload and No Construct Overload Model in Familiar Domain

Table 6 presents descriptive statistics for dependent measures in unfamiliar domain. We undertook one way ANOVA test to know the difference between groups, construct overload and no construct overload model in each unfamiliar and unfamiliar domain. Controlling the effect of familiar domain, we compare the comprehension accuracy, total score, of construct and no construct model in unfamiliar domain. As shown in table 7, for comprehension accuracy, the difference between the two groups, construct overload and no construct overload, was not statistically significant using ANOVA test (F = 0.005, sig = 0.946, p = 0.1).

Familiar Domain Construct-Overload vs. No Construct Overload	Mean	Std. Deviation	N
Construct-Overload	8.57	1.741	37
No Construct-Overload	8.54	1.643	37
Total	8.55	1.681	74

[Table 6] Descriptive Statistics for Dependent Measures: Unfamiliar Domain

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.910a	2	.455	.157	.855
Intercept	242.096	1	242.096	83.695	.000
Covariate (familiar Domain Construct Overload Vs. No Construct Overload)	.897	1	.897	.310	.579
Unfamiliar Domain Construct Overload Vs. No Construct Overload	.014	1	.014	.005	.946
Error	205.347	71	2.893		
Total	5621.000	74			
Corrected Total	206.284	73			

a. R Squared = .004 (Adjusted R Squared = -.024) ※ *p<0.1, **p<0.05, ***p<0.01

[Table 7] Accuracy Performance between Construct Overload and No Construct Overload Model in Unfamiliar Domain

In summary, strong support was achieved for the proposition based on problem-solving performance. If construct overload is predictive of human performance in problem-solving tasks using a conceptual model, we would expect to see a majority of statistically significant results among all of the tests conducted. However, it does not on both domains, familiar and unfamiliar domain. This finding strongly indicates that construct overload is not a prominent factor of human performance in a modeling context.

5. Cognitive Process Tracing Study

This study performed a process tracing study to better recognize the cognitive behavior patterns of practitioners and to acquire insights that could hardly be gained through quantitative analysis regarding the effect of treatment, construct overload. The purpose of process tracing study was to achieve a deeper understanding of practitioners' thought processes when they tried to solve the problems.

5.1. Design and Measures

We collected data about the cognitive processes of participants who contributed in our research using verbal protocol and eye tracking techniques. The verbal protocol technique requires participants to verbalize their thoughts when they perform some tasks (Ericsson and Simon, 1993), and it is used to compare cognitive search activities between two groups (Ericsson and Simon, 1993; Harte et al., 1994; Suh and Park, 2017). It is based on the assumption that humans intentionally form a representation of a problem and their detailed problem-solving strategies when they solve a problem and make a decision (Soelberg, 1965: Shanks et al., 2010, Suh and Park 2017) and humans can access these strategies and verbalize them (Shanks et al., 2010). This study uses the simultaneous verbal protocol method. Participants are asked to speak aloud during the problem-solving stage, thereby providing the researchers with direct access to their thought processes (Ericsson and Simon, 1984; Newell and Simon, 1972).

In this research, we use the concurrent verbal protocol approach, a rich source of information about respondents' cognitive processes (Van Gog et al., 2005). Participants are asked to speak aloud during the course of task, thereby offering the researchers with direct access to their thought processes (Ericsson and Simon, 1984; Newell and Simon, 1972; Shanks et al., 2010). Our purpose of using the technique is (a) understanding the cognitive behavior of participants when they perform tasks in which a significant difference exists and (b) providing a detailed explanation about these outcomes (Suh and Park, 2017).

In addition, we use the eye- tracking, a technique whereby an individual's eye movements are measured so that the researcher understands where a person is looking at any given time, and how their eyes are moving from one location to another (Jacob and Karn, 2003; Poole and Ball, 2006; Cutrell and

Guan 2007; Suh and Park 2017). It assumes that what an individual is looking at indicates what person is attending to (Jacob and Karn, 2003). Recording eye-movements, therefore, could offer a dynamic trace of where a person's attention is being directed in relation to a visual display (Goldberg and Kotval, 1999), because the eye provides input for 90% of the information used in human cognitive activity (Levelt et al. 1999). In other words, eye-tracking techniques can be a proxy for a user's attention. The main measurements used in eye-tracking research are fixations and sequence information. Fixation, such as focus map and heat map, is moments when the eyes are relatively stationary and sequence information, such as scan path and sequence chart, is an eye-tracking metric, usually a complete sequence of fixations and interconnecting saccades (Zhang and Marchionini, 2005). Fixations can be interpreted differently depending on the context, in an encoding task (e.g., understanding ER-Diagram), however, more fixations on a particular area indicate that it is more noticeable, or more important, to the participants than other areas (Poole et al, 1976). A sequence information can determine a participant's search strategy with entities, relationships and other interface elements (Altonen et al., 1998). In detail, our focus is on (a) investigating the part (e.g., construct overloaded part) at which intense concentration occurred and (b) understanding and examining the thought flow of participants and their search strategy.

5.2. Materials

We used the same four sets of experiment materials used in the quantitative analysis. The first set of materials comprised a personal profile questionnaire to gather information about participants' academic and industry qualifications. The second set is a summary of the ERD symbols that is presented in the diagrams. The third set of materials consists of four ER diagrams of a familiar domain (project management system) and an unfamiliar domain (waste processing system) where each domain consists of construct overload diagram. In case of eye tracking technique, all the four ER diagrams are presented on a screen. The fourth set of materials comprised 12 problem-solving questions of each domain.

5.3. Participants

Twelve and fourteen participants took part in the verbal protocol and eye tracking techniques each. All has at least six years' modeling experience. They were chosen on the basis that they played an important role in their organization as modelers and could act as surrogate for stakeholders.

5.4. Procedures

All the cognitive process approaches were pilot tested with four individuals who did not take part in the experiment. No concerns were recognized. The detailed process was similar to the procedure of non-protocol analysis participants; however, protocol analysis and eye-tracking were performed separately with research assistants.

Participants of verbal protocol were first assigned randomly one of the two models, construct overload or no construct overload model. When they arrive to undertake the task, they were given a consent form and a questionnaire to acquire demographic and experiential information. Then, the nature of the experiment and "speak-aloud" approach to data collection were explained. A cellphone acting as camcorder focused on the ER models and used to (a) record participants' verbalizations, and (b) videotape participants' behaviors. They were then given the document that explained the ER diagram symbols. If they had questions about symbols and examples, their questions were answered. This procedure continued until they felt confident about the ER diagrams. When participants suggested that they were ready to start, they were given either construct overload or no construct overload ER diagrams that reflected both familiar and unfamiliar domains. 12 protocol analysis participants were asked to speak aloud as they attempted to solve each problem-solving question, and their verbalizations and behaviors were recorded. If periods of silence occurred, research assistants reminded them to "speak aloud" to explain their cognitive behaviors. After a short pause at the conclusion of the first task, familiar or unfamiliar domain, participants were asked to complete the second task. Finally, they were thanked and dismissed. On average, it took about 55 minutes to complete both the familiar and unfamiliar questionnaires.

Before assigned one of the two models, participants of eye tracking techniques were given the document that explained the ER diagram symbols and completed demographic and consent forms. After, they fully understood the ER diagram, construct overload or no construct overload model was randomly assigned to them. Then, each participant received a short explanation of eye-tacking technique and was tested to determine whether his/her eyes could be accurately calibrated (if not, we ended the study). If the eye calibration succeeded, participants were asked to solve each problem-solving question, with their eye movement captured. Only ER-Diagrams were displayed on a computer screen and paper questionnaire is given to participants. To record the sequence information, participants were asked to solve the problem in numerical order. After finishing the first task, computer screen is turned off and then participants completed the second task. At the conclusion of this task, participants were thanked and dismissed. On average, it took about 60 minutes to complete both t questionnaires.

The experiment was conducted using a Dell computer running under Windows 7. The computer is equipped with an eye tracking system from SMI REDn Scientific(60 Hz) which includes an eye tracking camera, an SMI system for eye calibration, and a GazeTracker for data collection. Participants' task performance was recorded using iViewRED software.

5.5. Coding Scheme

A coding scheme was established based on the problem-solving literature (Newell and Simon, 1972) and previous research pertaining to conceptual modeling (Batra and Davis, 1992; Shanks et al. 2010, Suh and park, 2017). In our research, considering the volume of data, episodes were selected for use as the unit of analysis, a small self-contained phase of highly organized activity (Newell and Simon, 1972). The assumption of the coding scheme was that concurrent verbal protocol may indicate the problem space for which the participant is currently looking (Kim et al. 2000, Suh and Park 2017). A specific example of the protocol analysis is presented in Appendix A.

According to participant statements, each episode was classified as one of the following:

- *Understanding Question Level*: During the understanding question phase, the participant reads the question, considers the requirements and identifies assumptions. The focus at this level is on developing a reasonable understanding of the problem.

- *Recognizing Level*: In this phase, the participant focuses on some specific parts of the model, establishing connections with the key concept of the question. This triggers the suitable knowledge in a subject's repertoire.
- *Representing Level*: During the representation phase, the participant verifies the semantics of symbols in the model and develops solutions. Participants also re-read the question or the summary of the ER diagram symbol. This activates operationalization of the subject's deep understanding of the model into a conceptual data representation using the ER diagram.
- *Evaluating Level*: This phase includes development of solution and verification of the answer to ensure it satisfies the user requirements or the selection of alternative answers.

5.6. Analysis of Protocol Data

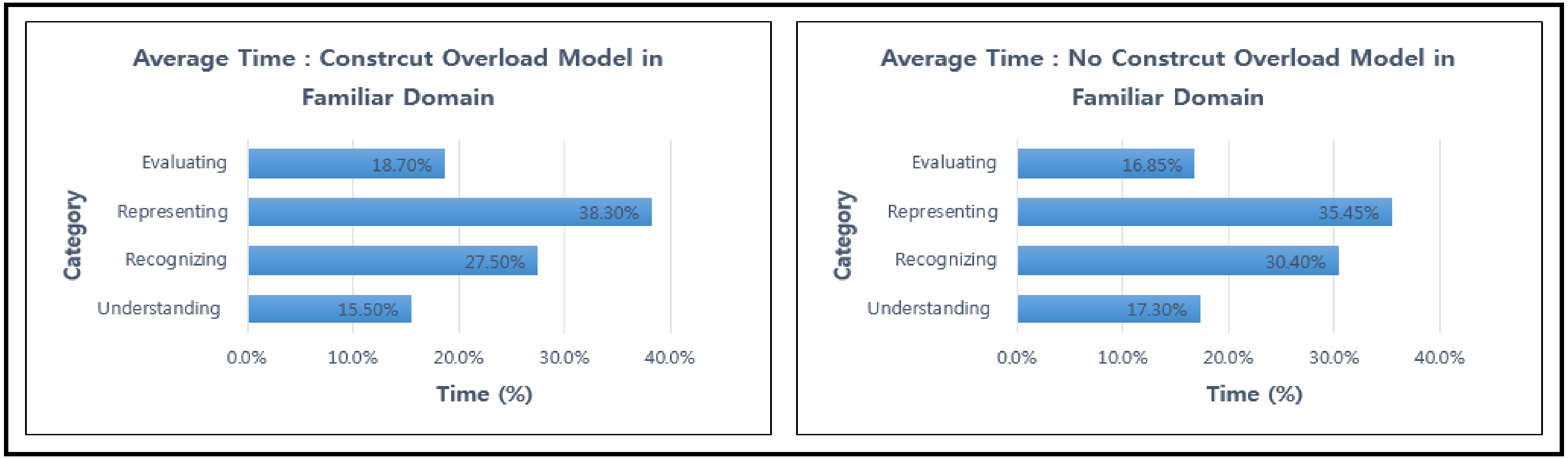
Qualitative data analysis was performed to obtain insights that could hardly be gained through quantitative analysis, regarding the effect of treatment, construct overload. The purpose of protocol analysis was to obtain a deeper understanding of participants' thought processes when they tried to solve the problems. The protocol data was analyzed in two ways. First, the average time participants spent in each of the four cognitive behavior categories was compared. The result may be the indicator in deciding in which category the main differences occurred. Second, the total numbers of transitions between each of the four cognitive behavior categories were compared. The result may be an indicator of sequence patterns of cognitive behavior.

The average time that participants spent in each cognitive behavior category is presented in figures 10 and 11. Participants who received the construct overload model in a familiar domain took 23.8 minutes to complete all 12 problem-solving questions, and those who received the no construct overload model took 23.5 minutes. Those who received the construct overload model in unfamiliar domains took 28.9 minutes to complete all 12 problem-solving questions, and those who received the no construct overload model took 31.3 minutes.

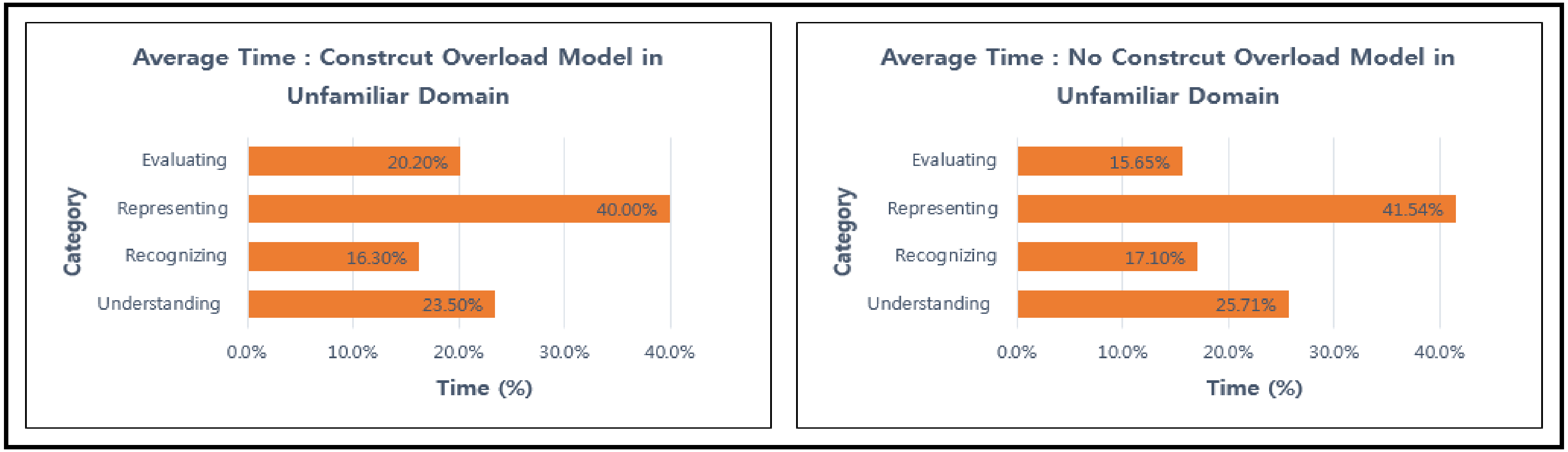
In both familiar and unfamiliar domains, the data proposed that although there was no remarkable difference in the total time taken between two models in each domain, there was a difference in the completion time of each represented category. In detail, participants who received the construct overload model in a familiar domain spent 38.30 percent (compared to 35.45 percent for participants who received no construct overload model) of their time validating semantics of symbols in the model and developing solutions. Participants who received the construct overload model in an unfamiliar domain spent 40.00 percent (compared to 41.54 percent for participants who received the no construct overload model) of their time verifying semantics of symbols in the model and finding solutions. These results may prove that the construct overload model called for a deeper understanding from participants than the no construct overload model in familiar domain, but in unfamiliar domain, though each construct in the ontology was not mapped to one construct in the grammar, construct overload model needed similar understanding compare to the no construct overload model. However, participants who received the construct overload model spent more time evaluating the solution especially in unfamiliar domain, which suggests that they have a little confidence in their thought processes. As a result, although the construct overload model may not promote greater understanding, assurances did not follow to its answer.

The sequential dependencies between four behavior categories is presented in figures 12 and 13. The numbers below the dependency arrows are the total numbers of transitions between two categories. The intensity of the dependency is represented by arrow thickness. In the case of familiar domain, the pattern and total number of transitions are similar between the two models. Generally, the most common sequence for participants, regardless of the type of model, was in recognizing and representing the model. This demonstrated that participants focus on specific areas related to certain questions and then try to develop and verify the answers by examining the model itself and using their own knowledge. Participants who received the construct overload model in the familiar domain had less transition activity during the recognizing and representing model segment for the cognitive behavior category. For instance, the construct overload model had 64 transitions in and 62 transitions out of the recognizing model segment for the cognitive behavior category compared to 68 transitions in and 65 transitions out among participants who received the no construct overload model. They also had 49 transitions in and 48 transitions out of the representing model segment compared to 53 transitions in and 52 transitions out. These results indicate that participants who received the construct overload model in the familiar domain focused less on finding connections with the key concept of the question, verifying semantics of symbols in the model and developing solutions. These results indicate that participants who had high domain knowledge about the construct overload model struggle less to verify the model by matching the proper model section.

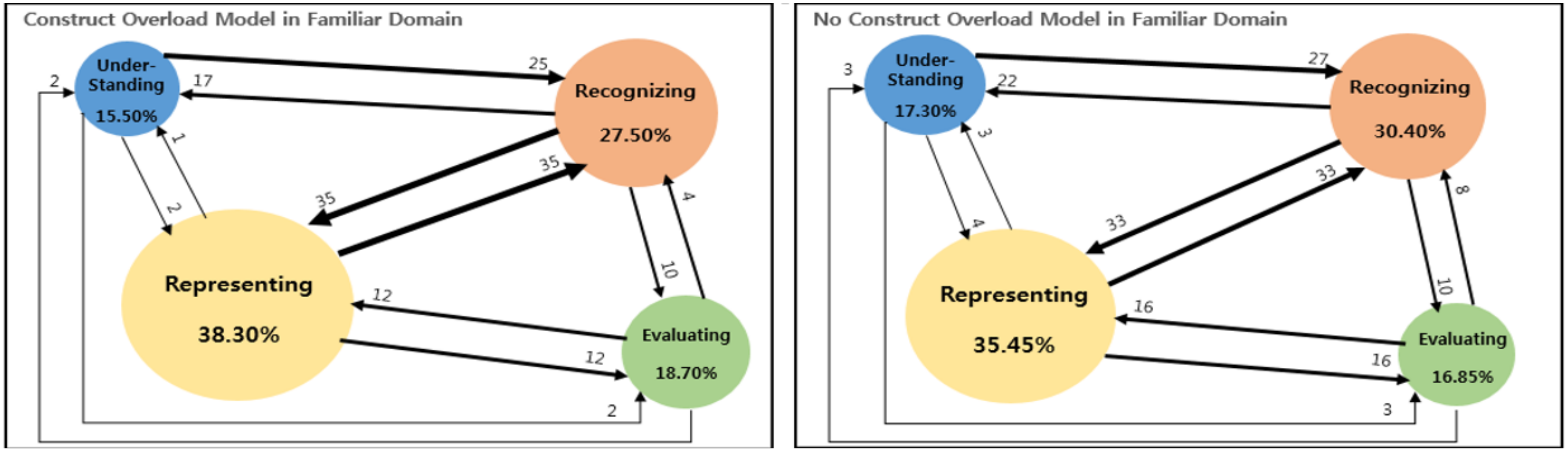
In the unfamiliar domain, the total number of transitions between each behavior was about one and half times more than that of transitions between each behavior in the familiar domain, because they hardly apply their background knowledge to solve the problem. However, the pattern and the total number of transitions are similar between construct overload and no construct overload models in the unfamiliar domain. The main difference of transition activity between the two models is recognizing and representing as well as representing and evaluating action. Specifically, participants who received the construct overload model had more transition activity between the recognizing and representing model segment than participants who received the no construct overload model. These results indicate that participants who had low domain knowledge about the construct overload model did have more difficult to verify the model by matching the proper model section than no construct overload model. Also, participants focused a bit more on transition activity in evaluating the construct overload model. This outcome indicate that construct overload model has some difficult to develop a solution and participants have low confidence in the answers.



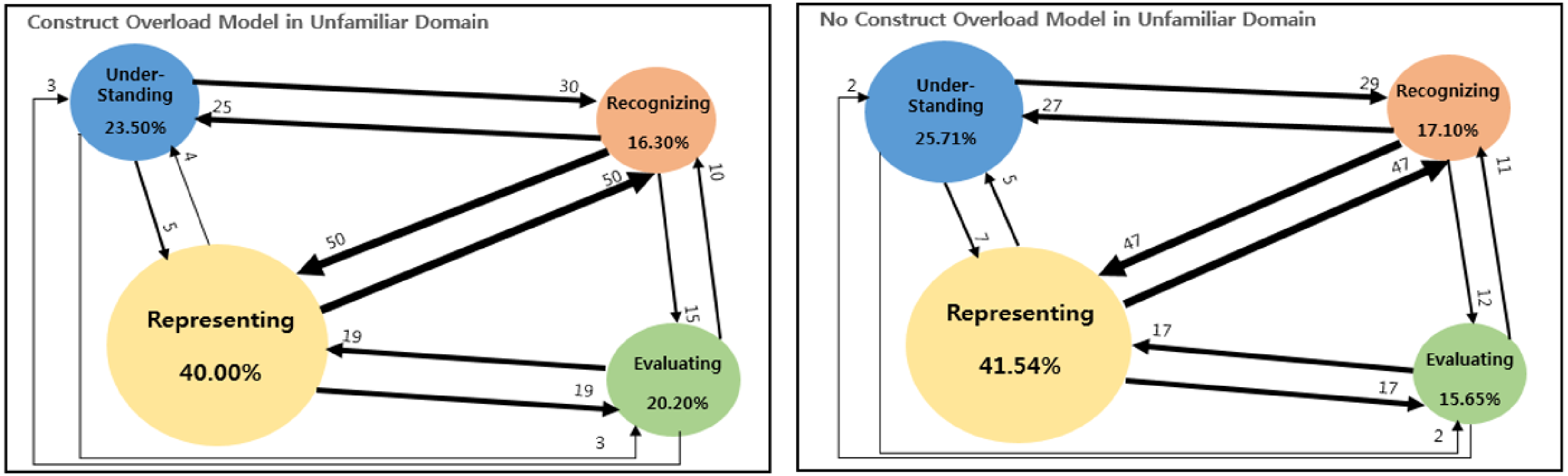
[Figure 10] Average Time that Participants Spent in each Cognitive Behavior Category: Familiar Domain



[Figure 11] Average Time that Participants Spent in each Cognitive Behavior Category: Unfamiliar Domain



[Figure 12] Sequential Dependencies between Four Behavior Categories: Familiar Domain

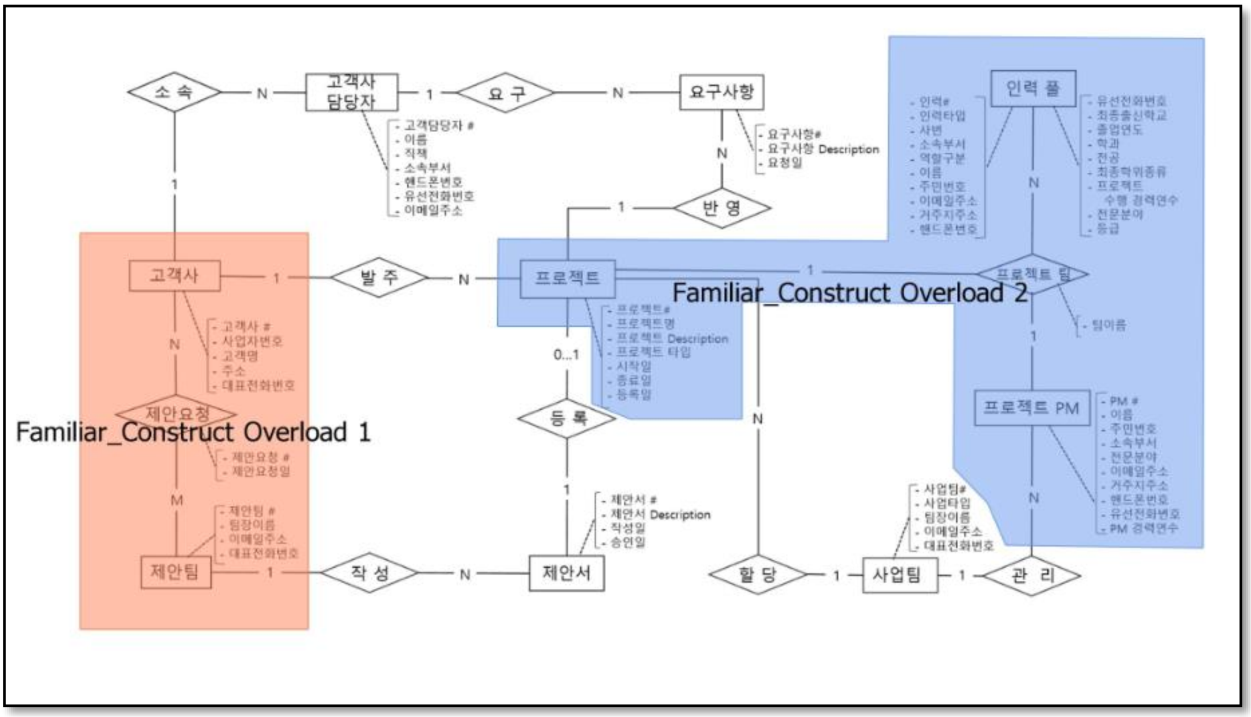


[Figure 13] Dependencies between Four Behavior Categories: Unfamiliar Domain

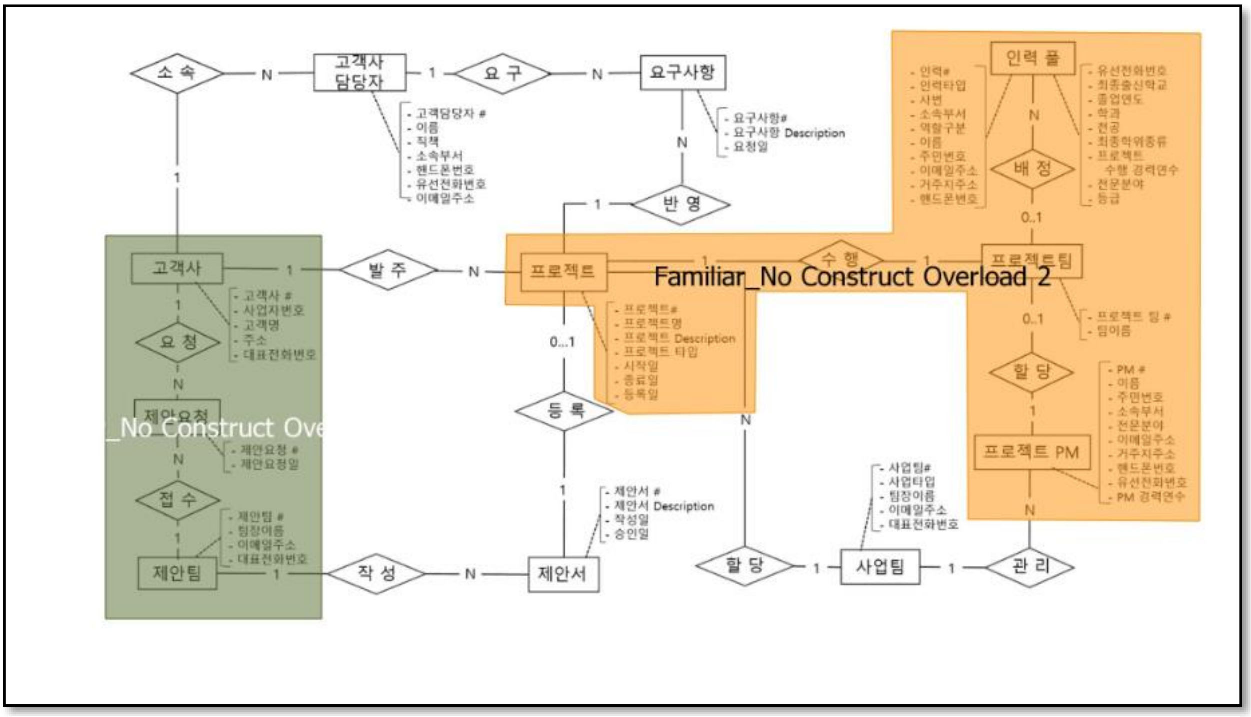
5.7. Analysis of Eye-tracking Data

Eye tracking was performed to understand participants viewing and cognitive behavior, regarding the effect of treatment, construct overload. Recording eye-movements provided a dynamic trace of where a person's attention and perception is being directed in relation to a visual display such as a conceptual model, because the eye gives input for 90% of the information used in human cognitive activity (Levelt et al. 1999). The purpose of eye-tracking, therefore, was to acquire an information and obtain a deeper understanding regarding user's attention and cognition.

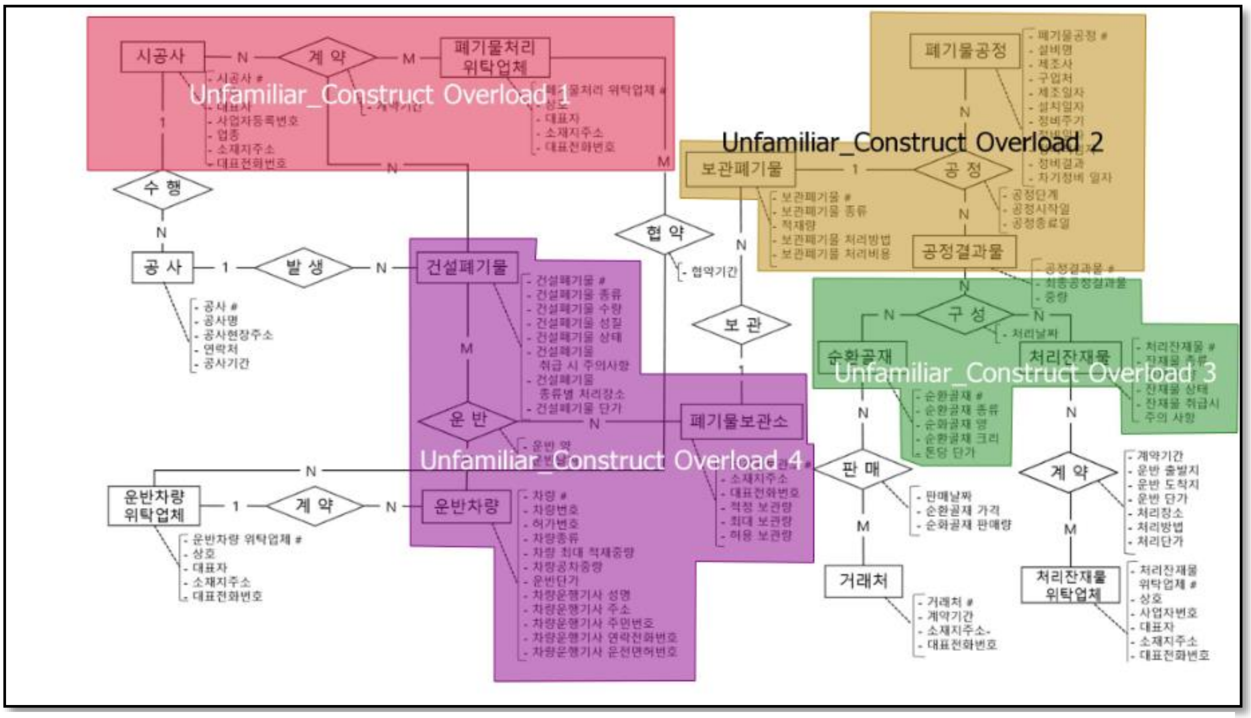
The eye-tracking was analyzed in three ways. First, the scan path displaying a sequential gaze data overlay over the stimulus image, conceptual model was analyzed. Second, the focus and heat map showing gaze patterns over the conceptual model was examined. In the focus map, when fixation duration become longer, the color becomes brighter and in the heat map, when fixation duration become longer, the color is changed from blue to red. Focus and heat map provide the model difficulty of delivering and communicating the meaning to reader because a longer fixation duration indicates difficulty in extracting information. In other words, it is challenging for the participant to verify the semantics of symbols in the model and develop solutions. Third, key performance indicators regarding AOI (Area of Interests) are analyzed. We defined two and four AOI (Area of Interests) respectively, because two (calls for project, project team) and four (contracts, transports, consists of, processes,) construct overloaded constructs were existed, in familiar and unfamiliar domain. Figure 14, 15, 16, and 17 present area of interest of construct overload models in familiar and unfamiliar domains individually. And then key performance indicators representing relevant statistical data for each defined AOI over the conceptual model were analyzed. We average the key performance indicators of fourteen participants regarding construct overload and no construct overload models in both domains. Table 8 shows the key performance indicators. Through three analyses of eye tracking, we could evaluate the participants' performance of conceptual model and understand the cognitive process on existence of construct overload in the conceptual model.



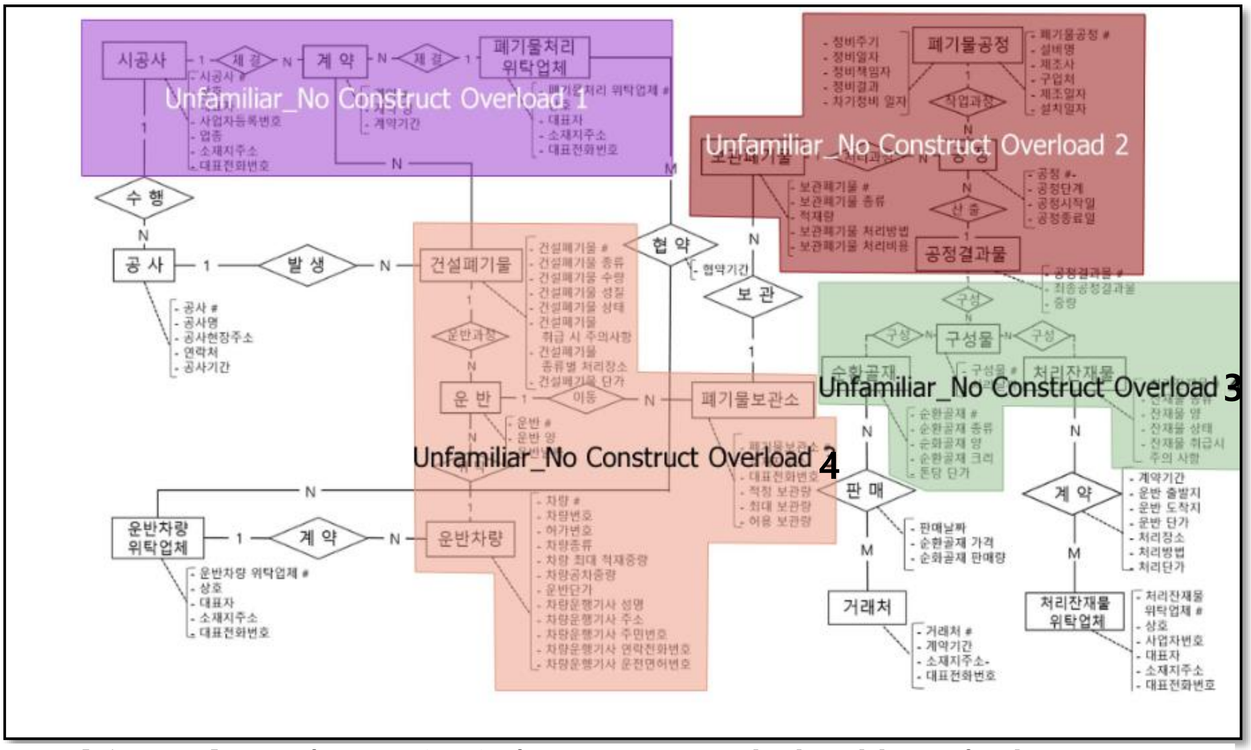
[Figure 14] Area of Interest (AOI) of Construct Overload Model in Familiar Domain



[Figure 15] Area of Interest (AOI) of No Construct Overload Model in Familiar Domain



[Figure 16] Area of Interest (AOI) of Construct Overload Model in Unfamiliar Domain



[Figure 17] Area of Interest (AOI) of No Construct Overload Model in Unfamiliar Domain

Sequence	Order of gaze hits into the AOIs based on entry time.
Entry time	Average duration for the first fixation in the AOI. Identify time spent on first fixation in the AOI.
Dwell time	The sum of all fixations and saccades within the AOI. Identify the visual attention for the participant.
Hit ratio	How many participants looked at least one time into the AOI. Identify the use of AOIs.
Revisits	How many visits the participants made into the AOI. Identify the use of AOIs with regards to glances.
Average fixation	The average of the fixation time in the specific AOI. Identify mental and cognitive workload
First fixation	How long the first fixation for selected participants in AOI lasted. Identify patterns and workloads.
Fixation count	Number of all fixations in AOI. Identify complexity of AOI.

[Table 8] Key Performance Indicators of Eye Tracking Technique

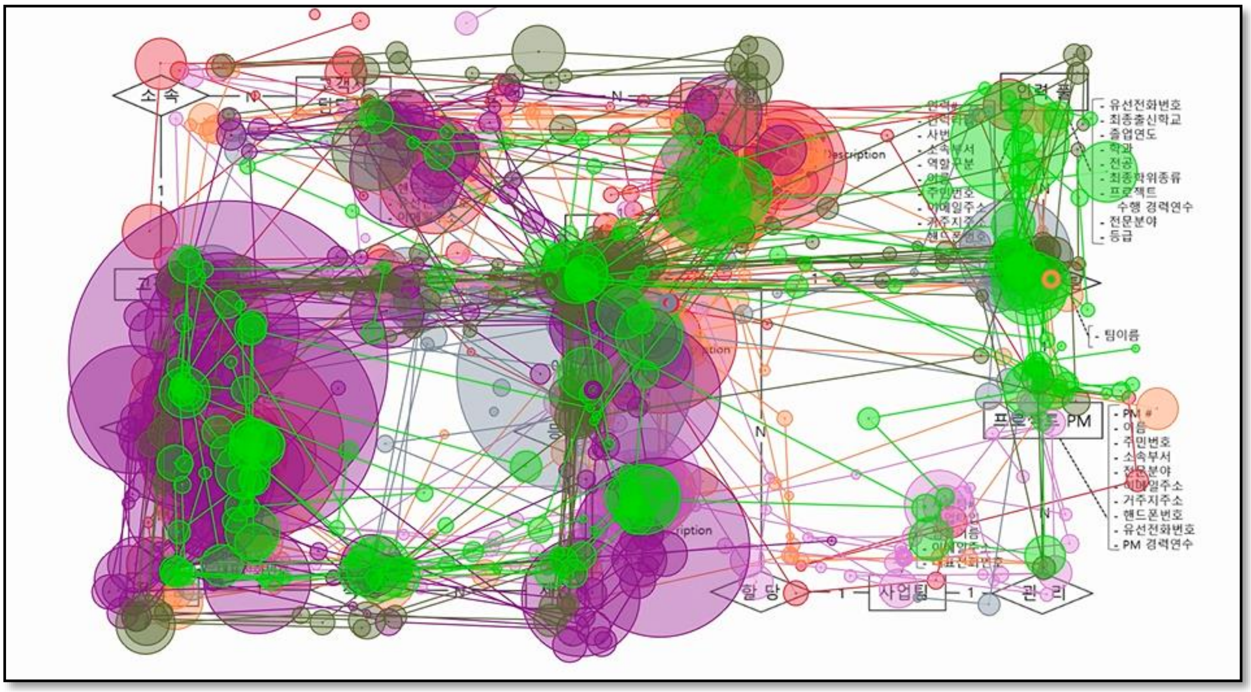
Scan Path

The scan path provided the sequence in which the spot was viewed by the each participant and recorded the time spent on a gaze spot area. The time comparison on a gazing is the signal of thinking processing (Goldberg & Kotval, 1999). In other words, smaller size of the gaze spot means that less time spent on viewing the area and cognitive processing, whereas bigger size of the gaze spot indicates that more time spent on viewing and cognitive processing (Goldberg & Kotval, 1999).

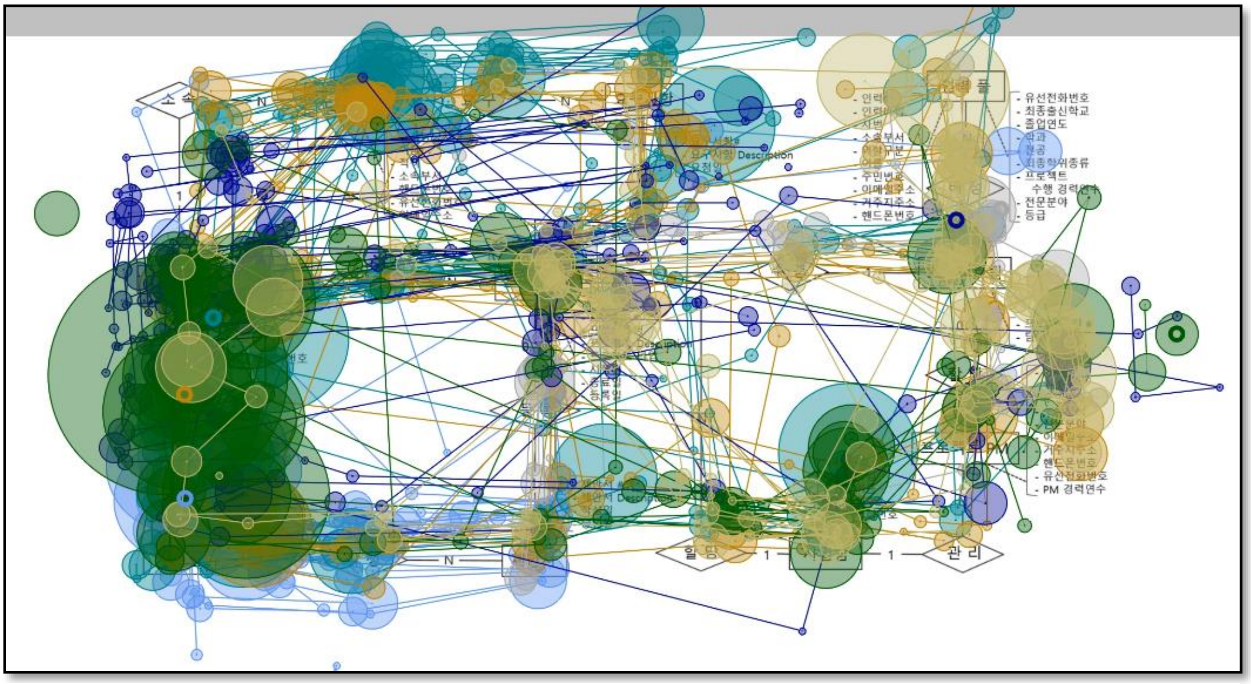
In familiar domain, it was hard to recognize the different path sequence between construct overload and no construct overload models, attributed to the fact that the participants of each model solve the problems in sequence-number order. Regarding size of the gaze spot, two construct overload spots presented in relationship on construct overload model and presented in entity on no construct overload model were similar in size, indicating that no difference in cognitive processing time between two models.

Figure 18 and 19 present the results of seven participants' scan path in familiar domain.

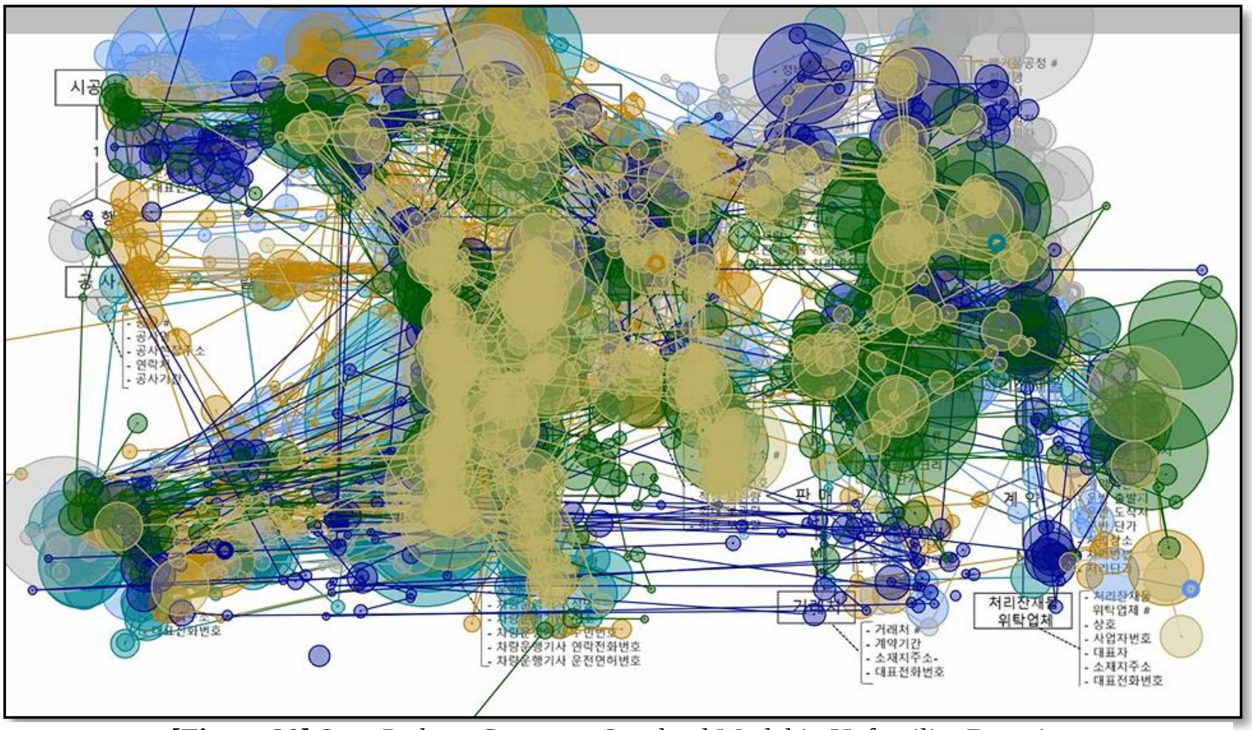
The path sequences between two models in unfamiliar domain are similar to those of familiar domain models stemming from solving the question in numerical order. The size of the gaze spot between two models is somewhat different. In detail, the number of smaller spots in construct overload model is greater than in no construct overload model, meaning that in unfamiliar domain, construct overload model requires some cognitive loads during the processing. As the size of gaze spot, however, is small, it does not need much time to process the construct overload domain. Figure 20 and 21 present the results of seven participants' scan path in unfamiliar domain



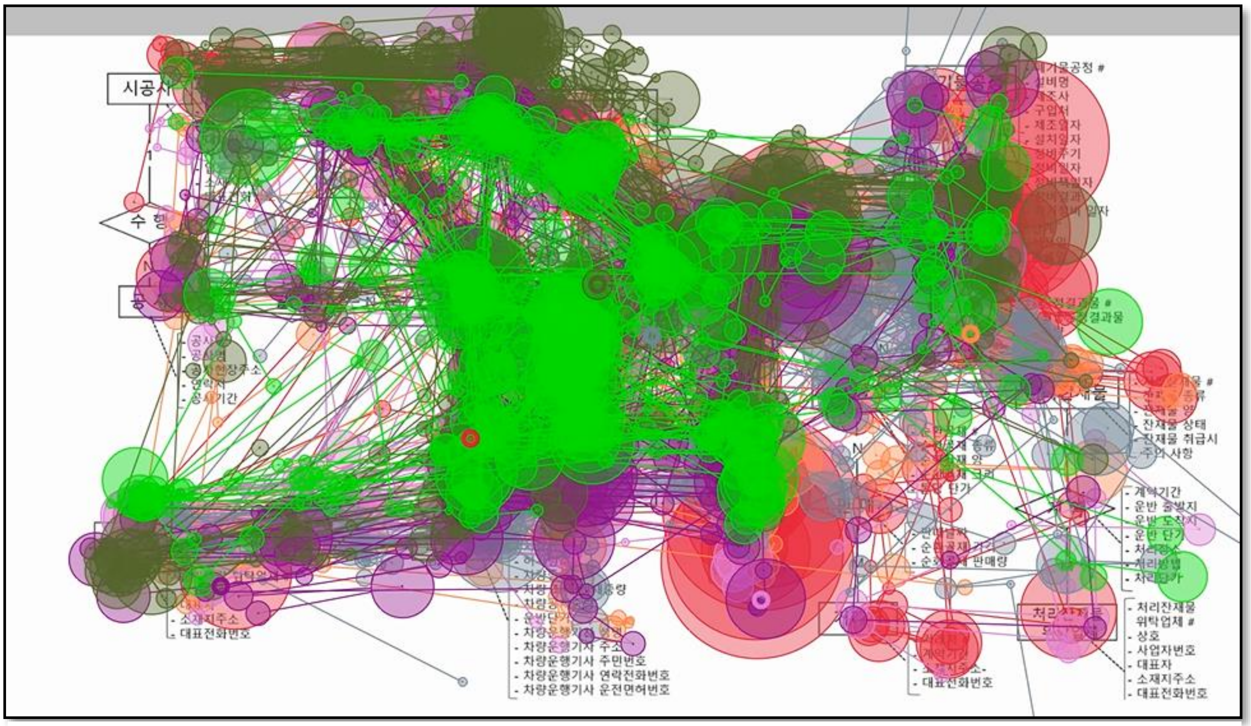
[Figure 18] Scan Path on Construct Overload Model in Familiar Domain



[Figure 19] Scan Path on No Construct Overload Model in Familiar Domain



[Figure 20] Scan Path on Construct Overload Model in Unfamiliar Domain



[Figure 201] Scan Path on No Construct Overload Model in Unfamiliar Domain

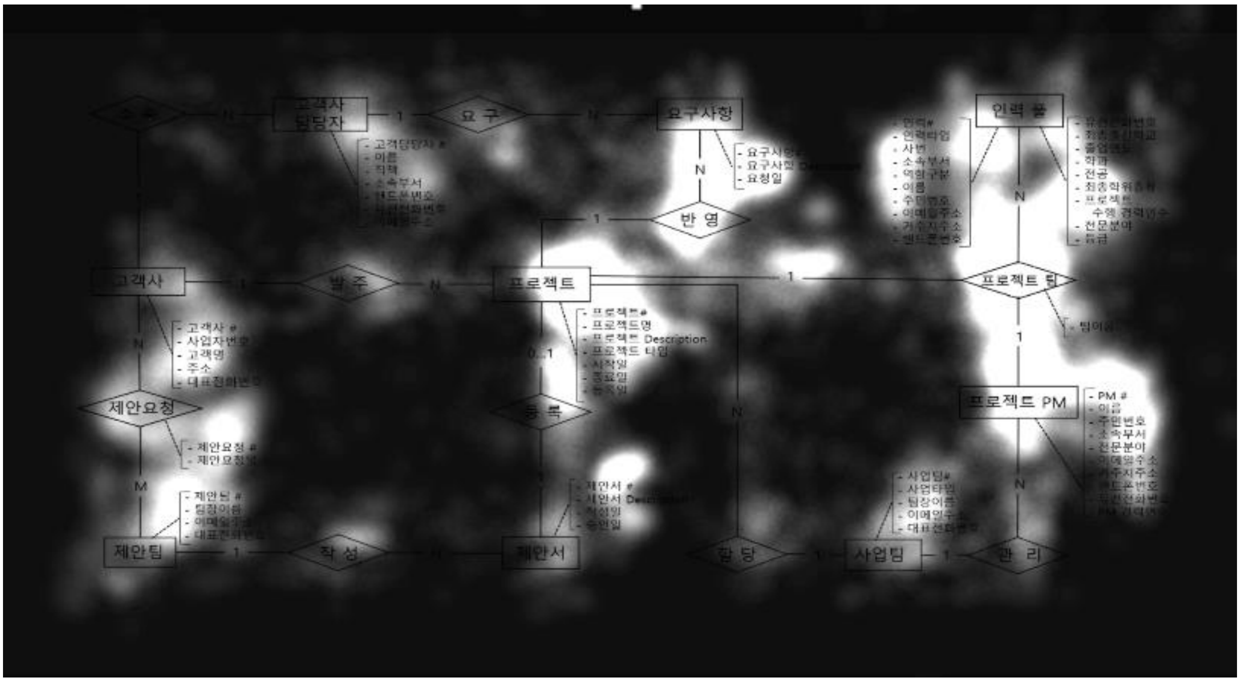
Focus and Heat Map

Focus and heat map provide the model difficulty of delivering and communicating the meaning to reader because a longer fixation duration indicates difficulty in extracting information. In other words, it is challenging for the participant to verify the semantics of symbols in the model and develop solutions. Also, focus and heat map are visualizations which present the overall distribution of fixations and gaze points, they are, therefore, indicators of someone's attention and the excellent method to recognize which constructs attract more attention than others (Jacob and Karn, 2003).

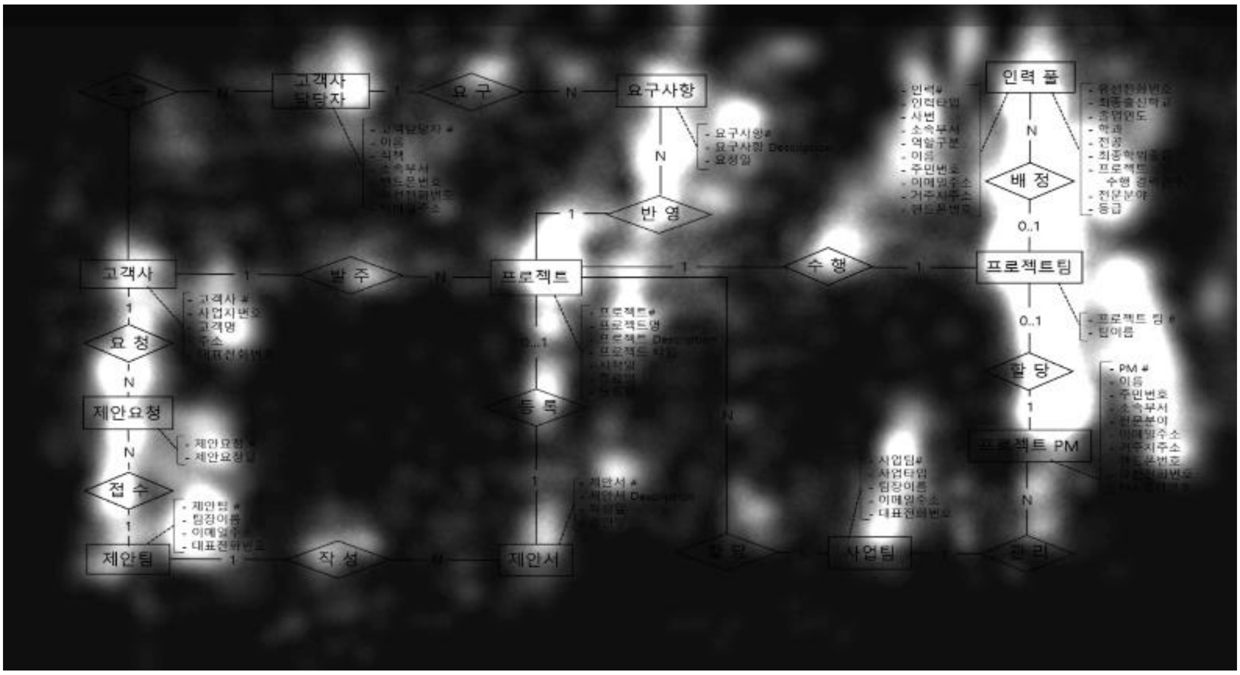
In case of focus map, more fixations lead to a clearer view of the page and darker areas indicate fewer fixations i.e. decreased level of attention, and in case of heat map, red areas suggesting a high number of gaze points i.e. increased level of attention, followed by yellow and blue (Goldberg & Kotval, 1999). Figure 22 and 23 present the focus maps on construct overload and no construct overload models in familiar domain. It is difficult to compare the transparency of two models, because of expression technique, black and white, therefore, we focus on the heat map using color-shaded matrix display.

Figure 24 and 25 show the heat maps on construct overload and no construct overload models in familiar domain. The size of red area is different in construct overload part, project team. In detail, project team represented in relationship presents small size of red compare to project team represented in entity, showing that no construct overload model requires more attention than construct overload model. In other words, when users can apply his/her domain knowledge to model, one to one mapping between conceptual grammar construct and ontological construct require more attention.

Figure 26 and 27 present the heat maps on models in unfamiliar domain. As familiar domain, the size of red area is different in construct overload part, transports, process and consists of. By comparison, more attention and model difficulty occurred in conveying the meaning for participants who received the no construct overload model.

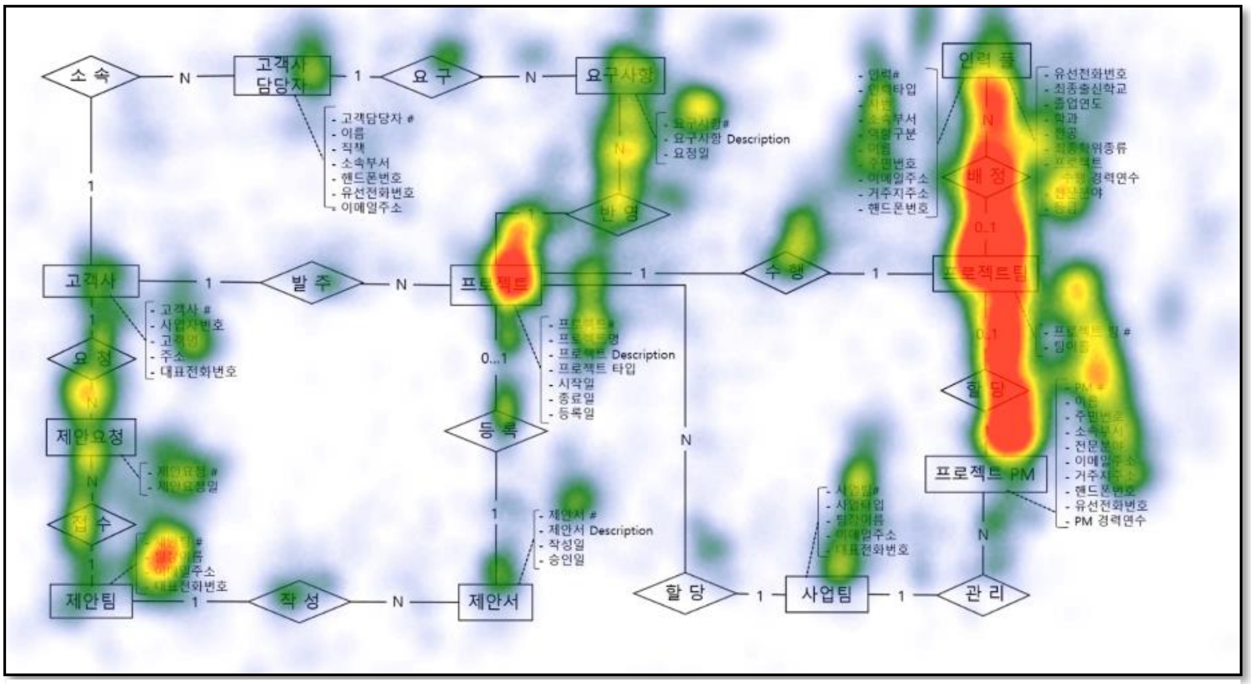


[Figure 21] Focus Map on Construct Overload Model in Familiar Domain

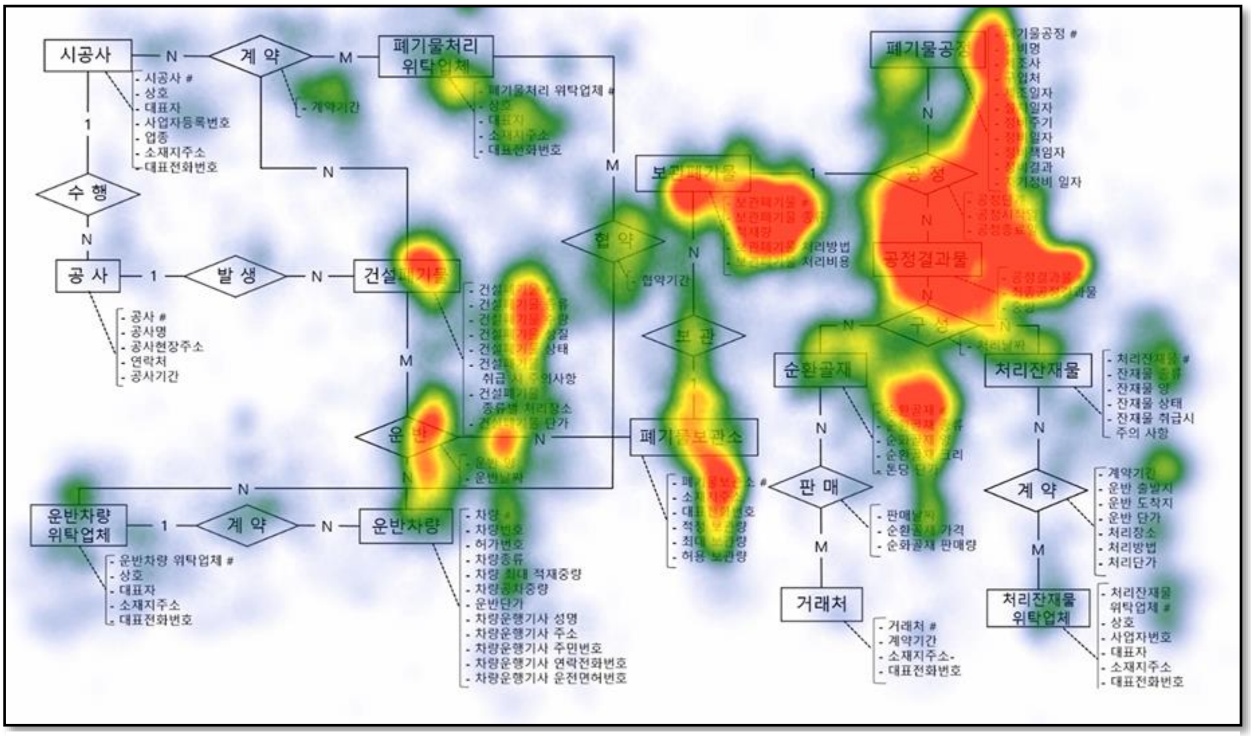


[Figure 22] Focus Map on No Construct Overload Model in Familiar Domain

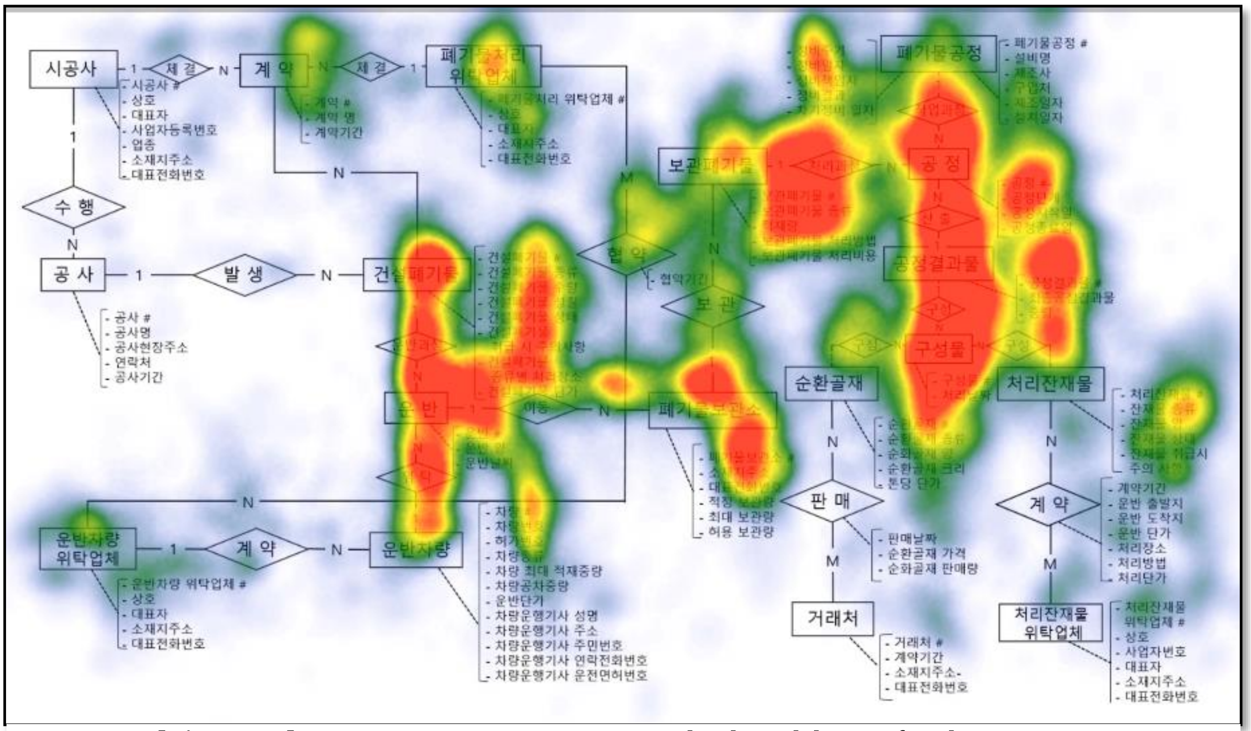
[Figure 24] Heat Map on Construct Overload Model in Familiar Domain



[Figure 25] Heat Map on No Construct Overload Model in Familiar Domain



[Figure 24] Heat Map on Construct Overload Model in Unfamiliar Domain



[Figure 23] Heat Map on No Construct Overload Model in Unfamiliar Domain

Quantitative Data Analysis of Key Performance Indicators

Key performance indicators (KPIs) of eye tracking technique display relevant statistical data for each defined AOI over the stimulus image, conceptual model and deliver both quantitative and qualitative information on visual behavior and impact. As we indicated above, table 6 presents the key performance indicator of eye tracking technique and table7 and 8 show the mean of each KPI statistics. Among eight indicators, we analyze dwell time, average fixation, and fixation count, because they identify the the participants' mental and cognitive workload and complexity of AOI respectively.

Area of Interest	Sequence	Entry time [ms]	Dwell time [ms]	Hit ratio [%]	Revisits	Average fixation [ms]	First fixation [ms]	Fixation count
Familiar Domain Construct Overload 1	3	35286	25674	100	20	356	278.4	66
Familiar Domain No Construct Overload 1	3	17867	46013	100	26	442	373.7	64
Familiar Domain Construct Overload 2	2	9807	174012	100	96	313	261.8	507
Familiar Domain No Construct Overload 2	2	8359	198309	100	101	327	387.8	582

[Table 9] KPI Statistics of Familiar Domain AOIs

Area of Interest	Sequence	Entry time [ms]	Dwell time [ms]	Hit ratio [%]	Revisits	Average fixation [ms]	First fixation [ms]	Fixation count
Unfamiliar Domain Construct Overload 1	2	10403	34399	100	38	277	159.5	117
Unfamiliar Domain No Construct Overload 1	2	8326	37114	100	36	284	178.5	121
Unfamiliar Domain Construct Overload 2	5	45199	147446	100	82	379	240.4	353
Unfamiliar Domain No Construct Overload 2	4	18093	170113	100	87	385	278.5	451
Unfamiliar Domain Construct Overload 3	4	39108	60628	100	62	322	221.4	169
Unfamiliar Domain No Construct Overload 3	5	71507	79858	100	69	367	242.8	211
Unfamiliar Domain Construct Overload 4	3	16000	104700	100	85	304	288	332
U Unfamiliar Domain No Construct Overload 4	3	16175	102917	100	86	303	288	489

[Table 10] KPI Statistics of Unfamiliar Domain AOIs

In case of familiar domain, there are two AOIs respectively in construct overload and no construct overload model. Figure14 and 15 present two parts. We used an independent samples t-test and Mann-Whitney U-test as well as Wilcoxon signed rank test, non-parametric test, because we assume homoscedasticity of the population.

As shown in table 9, for dwell time, the difference between the two groups, construct overload 1 and no construct overload 1, was not statistically significant using independent samples *t*-test (t = 0.044, sig = 0.666, p < 0.1) and was not statistically significant using Mann-Whitney U-test (z = -0.38, Asymp. Sig. = 0.7010, p < 0.1). For average fixation, the difference between the two groups was statistically significant using independent samples *t*-test (t = -28.91, sig = 0.000, p < 0.01) and was statistically significant using Mann-Whitney U-test (z = -3.13, Asymp. Sig. = 0.0020, p < 0.01). For fixation count, the difference between the two groups was statistically significant using independent samples *t*-test (t = -10.5, sig = 0.000, p < 0.01) and was statistically significant using Mann-Whitney U-test (z=-3.14, Asymp. Sig. = 0.0020, p < 0.01)

For dwell time, the difference between the two groups, construct overload 2 and no construct overload 2, was not statistically significant using independent samples *t*-test (t = 0.86, sig = 0.406, p < 0.1) and was not statistically significant using Mann-Whitney U-test (z = -1.09, Asymp. Sig. = 0.2770, p < 0.1). For average fixation, the difference between the two groups was statistically significant using independent samples *t*-test (t = -7.861, sig = 0.000, p < 0.01) and was statistically significant using Mann-Whitney U-test (z = -3.15, Asymp. Sig. = 0.0016, p < 0.01). For fixation count, the difference between the two groups was statistically significant using independent samples *t*-test (t = -32, sig = 0.000, p < 0.01) and was statistically significant using Mann-Whitney U-test (z=-3.14, Asymp. Sig. = 0.0017, p < 0.01)

Familiar Domain	Control	N	Mean	Std. Deviation	*t*	Sig. (2-tailed)	Mean Difference	Mann-Whitney U	
								Z	Asymp. Sig. (2-tailed)
Dwell time [ms]	Construct Overload 1	7	304.43	8.4	0.44	0.666	1.86	-0.38	0.7010
	No Construct Overload 1	7	302.57	7.28					
Average fixation [ms]	Construct Overload 1	7	331.86	11.52	-28.91	0.000***	-156.71	-3.13	0.0020***
	No Construct Overload 1	7	488.57	8.54					
Fixation count	Construct Overload 1	7	169.43	6.95	-10.5	0.000***	-41.71	-3.14	0.0020***
	No Construct Overload 1	7	211.14	7.88					
Dwell time [ms]	Construct Overload 2	7	104699.71	4294.65	0.86	0.406***	1782.86	-1.09	0.2770
	No Construct Overload 2	7	102916.86	3404.80					
Average fixation [ms]	Construct Overload 2	7	313.43	4.20	-7.861	0.000***	-13.43	-3.15	0.0016***
	No Construct Overload 2	7	326.86	1.68					
Fixation count	Construct Overload 2	7	507.43	2.44	-32	0.000***	-74.14	-3.14	0.0017***
	No Construct Overload 2	7	581.57	5.62					

※ *p<0.1, **p<0.05, ***p<0.01

[Table 11] Dwell Time, Average Fixation, and Fixation Count of Two AOIs in Familiar Domain

In case of unfamiliar domain, there are four AOIs respectively in construct overload and no construct overload model. Figure16 and 17 present two parts. We used an independent samples *t*-test and Mann-Whitney U-test as well as Wilcoxon signed rank test, non-parametric test, because we assume homoscedasticity of the population.

As shown in table 10, for dwell time, the difference between the two groups, construct overload 1 and no construct overload 1, was statistically significant using independent samples *t*-test ($t = -4.73$, sig = 0.000, $p < 0.01$) and was statistically significant using Mann-Whitney U-test ($z = -3.13$, Asymp. Sig. = 0.002, $p < 0.01$). For average fixation, the difference between the two groups was not statistically significant using independent samples *t*-test ($t = -1.53$, sig = 0.151, $p < 0.1$) and was not statistically significant using Mann-Whitney U-test ($z = -1.47$, Asymp. Sig. = 0.141, $p < 0.01$). For fixation count, the difference between the two groups was not statistically significant using independent samples *t*-test ($t = -0.83$, sig = 0.425, $p < 0.1$) and was not statistically significant using Mann-Whitney U-test ($z = -0.83$, Asymp. Sig. = 0.405, $p < 0.1$)

For dwell time, the difference between the two groups, construct overload 2 and no construct overload 2, was statistically significant using independent samples *t*-test ($t = -7.26$, sig = 0.000, $p < 0.01$) and was statistically significant using Mann-Whitney U-test ($z = -3.13$, Asymp. Sig. = 0.002, $p < 0.01$). For average fixation, the difference between the two groups was not statistically significant using independent sample *t*-test ($t = -1.15$, sig = 0.274, $p < 0.1$) and was not statistically significant using Mann-Whitney U-test ($z = -1.41$, Asymp. Sig. = 0.158, $p < 0.1$). For fixation count, the difference between the two groups was statistically significant using independent samples t-test ($t = -23.04$, sig = 0.000, $p < 0.01$) and was statistically significant using Mann-Whitney U-test ($z=-3.13$, Asymp. Sig. = 0.002, $p < 0.01$)

For dwell time, the difference between the two groups, construct overload 3 and no construct overload 3, was statistically significant using independent samples *t*-test ($t = -7.26$, sig = 0.000, $p < 0.01$) and was statistically significant using Mann-Whitney U-test ($z = -3.13$, Asymp. Sig. = 0.002, $p < 0.01$). For average fixation, the difference between the two groups was not statistically significant using independent samples *t*-test ($t = -1.53$, sig = 0.151, $p < 0.1$) and was not statistically significant using Mann-

Whitney U-test ($z = -1.47$, Asymp. Sig. = 0.141, $p < 0.1$). For fixation count, the difference between the two groups was statistically significant using independent samples *t*-test ($t = -23.04$, sig = 0.000, $p < 0.01$) and was statistically significant using Mann-Whitney U-test ($z=-3.13$, Asymp. Sig. = 0.002, $p < 0.01$)

For dwell time, the difference between the two groups, construct overload 4 and no construct overload 4, was statistically significant using independent samples *t*-test ($t = -4.73$, sig = 0.000, $p < 0.01$) and was statistically significant using Mann-Whitney U-test ($z = -3.13$, Asymp. Sig. = 0.002, $p < 0.01$). For average fixation, the difference between the two groups was not statistically significant using independent samples t-test ($t = -1.15$, sig = 0.274, $p < 0.1$) and was not statistically significant using Mann-Whitney U-test ($z = -1.41$, Asymp. Sig. = 0.158, $p < 0.1$). For fixation count, the difference between the two groups was not statistically significant using independent samples *t*-test ($t = -0.83$, sig = 0.425, $p < 0.1$) and was not statistically significant using Mann-Whitney U-test ($z=-0.83$, Asymp. Sig. = 0.405, $p < 0.1$)

Unfamiliar Domain	Control	N	Mean	Std. Deviation	t	Sig. (2-tailed)	Mean Difference	Mann-Whitney U	
								Z	Asymp. Sig. (2-tailed)
Dwell time [ms]	Construct Overload 1	7	34399.29	747.05	-4.73	0.000***	-2714.86	-3.13	0.002***
	No Construct Overload 1	7	37114.14	1323.65					
Average fixation [ms]	Construct Overload 1	7	276.57	11.87	-1.53	0.151	-7.71	-1.47	0.141
	No Construct Overload 1	7	284.29	5.99					
Fixation count	Construct Overload 1	7	117	8.58	-0.83	0.425	-3.71	-0.83	0.405
	No Construct Overload 1	7	120.71	8.24					
Dwell time [ms]	Construct Overload 2	7	147445.57	4651.7	-7.26	0.000***	-22667.29	-3.13	0.002***
	No Construct Overload 2	7	170112.86	6820.02					
Average fixation [ms]	Construct Overload 2	7	379.14	10.4	-1.15	0.274	-5.71	-1.41	0.158
	No Construct Overload 2	7	384.86	8.13					
Fixation count	Construct Overload 2	7	352.57	6.08	-23.04	0.000***	-98.57	-3.13	0.002***
	No Construct Overload 2	7	451.14	9.55					
Dwell time	Construct Overload 3	7	147445.57	4651.7	-7.26	0.000***	-22667.29	-3.13	0.002***

[ms]	No Construct Overload 3	7	170112.86	6820.02					
Average fixation [ms]	Construct Overload 3	7	276.57	11.87	-1.53	0.151	-7.71	-1.47	0.141
	No Construct Overload 3	7	284.29	5.99					
Fixation count	Construct Overload 3	7	352.57	6.08	-23.04	0.000***	-98.57	-3.13	0.002***
	No Construct Overload 3	7	451.14	9.55					
Dwell time [ms]	Construct Overload 4	7	34399.29	747.05	-4.73	0.000***	-2714.86	-3.13	0.002***
	No Construct Overload 4	7	37114.14	1323.65					
Average fixation [ms]	Construct Overload 4	7	379.14	10.4	-1.15	0.274	-5.71	-1.41	0.158
	No Construct Overload 4	7	384.86	8.13					
Fixation count	Construct Overload 4	7	117	8.58	-0.83	0.425	-3.71	-0.83	0.405
	No Construct Overload 4	7	120.71	8.24					

※ *p<0.1, **p<0.05, ***p<0.01

[Table 12] Dwell Time, Average Fixation, and Fixation Count of Four AOIs in Unfamiliar Domain

6. Discussion

6.1. Conclusion

Semantics lies at the heart of conceptual modeling (Clarke et al., 2016). It offers the connection between our representations (models) and the reality they try to represent. It underpins the meaning that practitioners ascribe to representations. Previous methods to evaluate the semantics of conceptual model depend mainly on ontological clarity (Clarke et al., 2016, Suh and Park, 2017) indicating constructs of conceptual grammar exist in bijective correspondence with the constructs of an ontology.

Based on the above analysis of conceptual underpinnings, experimental procedures, and data analysis, we argue that there is sufficient evidence that construct overload is a not salient predictor of practitioners' performance regardless of their background knowledge, meaning the theory of ontological clarity has been falsified (Popper, 1963; Allen and March, 2012; Suh and Park, 2017) and must be modified to interoperate the new experimental findings.

6.2. Implication

Our result have implications for practice and research. The practical implications of our analysis are quite clear. We give strong support that construct overload does not matter to actual modeler, practitioners which will suggest a way in which information systems practitioners might build and validate the conceptual models they create. Specially, our results may serve as a modeler's ontological guidance in terms of whether or not to contain construct overload when they create and validate the model. For example, regardless of domain knowledge, the modeler can create a construct overload model.

This study give some research implications. First, we used Wand and Weber's theoretical work to speculate about construct overload of conceptual modeling grammar. We interpret our results as supporting evidence for the validity and usefulness of Wand and Weber's theory of ontological clarity in the research of conceptual modeling and related research. By establishing that construct overload does not hinder the practitioner's understanding of the conceptual model, we argue that Wand and Weber's theory allows researchers to speculate faithfully about conceptual modeling practices and outcomes (Recker et al., 2011, Suh and Park 2017), and it gives merit to researchers that when you try to build the theory, human context, such as background information, prior experience and level of understanding, must be considered together. (Burton-Jones et al., 2005; Tolman, 1959; Suh and Park, 2017)

Second, usage of construct overload on conceptual modeling produced some counterintuitive and controversial results (Clarke et al., 2016; Suh and Park, 2017), and these conflicting viewpoints were published in the same issue of *MIS Quarterly* in September 2012. In detail, Shanks et al. (2008) concluded that the bijective correspondence model, no construct overload model, allows user to better understand a domain. Allen and March (2012), however, came to the opposite conclusion of Shanks et al. (2008) and argued that using construct overload on conceptual model provided better performance. Therefore, construct overload in conceptual model remains an issue to be resolved. By performing the experiment to reduce the potential confounding effects from prior research, this study finally concluded construct overload dispute.

Third, as the development of measurement technologies, an emerging trend in cognitive psychology and information systems is to use neuroscience knowledge as a foundation to collect evidence for interpreting human behaviors (Zhao and Siau, 2016). Also, neuroscience method can provide evidence that is not available in traditional behavior or design science research, and give better measurement of existing constructs (Reidel et al., 2010). In other words, certain latent constructs measured by reflective indicators may be better assessed with neuroscience methods. Among neuroscience methods, eye tracking become a popular instrument in research such as attention, consciousness, learning, memory, decision making, emotion, language, and so on (Zhao and Siau, 2016). In this research, we used eye-tracking technique to understand participants' attention and awareness regarding the existence or nonexistence of construct overload when they solve the problem. By using this method, our study can provide evidence to examine existing issues from a different viewpoint.

6.3. Limitations and Future Research Directions

Future research work might be pursued in two directions. First, as we indicated above, comparing the difference in problem-solving processes on construct overload between practitioner and novice may contribute to a deeper understanding of what the novice does differently when compared to practitioner (Batra and Davis, 1992; Chi et al., 1988; Larkin et al., 1980; Suh and Park, 2017).

Second, this study employed two different domain familiarities, familiar (project management system) and unfamiliar (waste processing system), however, by subdividing the domain familiarity (such as three or five levels of domain familiarity) and investigating the differences between those familiarities, we could recognize the range of domain knowledge over each construct overload issue in detail.

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Appendix A

Summary of Information Processing Coding Typology

Category	Understanding Question Level	Recognizing Level	Representing Level	Evaluating Level
Content	Reading question; considering the requirements and identifying assumptions	Rephrasing the content with adding new information; focusing on some specific parts of the ER diagram	Re-reading the question or the summary of the ER diagram; making connections between question and ER-diagram; verifying semantics of symbols in the diagram and developing solution	Making judgments of the question; verifying the answer

Protocol Analysis Example

A participant solves the problem #1 of the construct overload model under the unfamiliar domain.

Research assistant: *Thank you for taking time from your busy schedule to meet with me. Look at each ER-Diagram and solve the problem. If you do not understand or don't know anything while you are solving problems, please let me know. And please keep saying anything while you are solving problems.*

Participant: Yes, I see. I will solve the problem inferring by myself. The domain is waste processing system. Um… It is difficult to make the problem on this domain… I will solve the problems in order. Number 1, construction company reduces the scope of the contract. So, renegotiation and reduce the contract with the consignment vendor? (making circle on the paper after turning over the front page and seeing conceptual model). It could be as a common sense but seems not to have to review attribute. There is nothing related but it would be all right contract and transports are connected. The answer is yes. Underlying the problem once again, compare with the front conceptual model. Let's go number 2.

Text	Category
Yes, I see	
*I will **solve** the **problem inferring** by myself.*	Understanding
*The **domain** is waste processing system.*	Understanding Recognizing
*Um… It is **difficult** to make the **problem** on this **domain**…*	Representing
*I will **solve** the problems in order.*	Recognizing

Number 1, construction company reduces the scope of the contract.	Recognizing
So, renegotiation and reduce the contract with the consignment vendor?	Representing
(making circle on the paper after turning over the front page and seeing conceptual model).	Recognizing Representing
It could be as a ***common sense*** *but seems not to have to* ***review attribute****.*	Representing
There is nothing related but it would be all right contract and transports are connected.	Representing
The ***answer*** *is yes. (Underlying the problem once again, compare with the front conceptual model.)*	Evaluating
Let's go number 2	

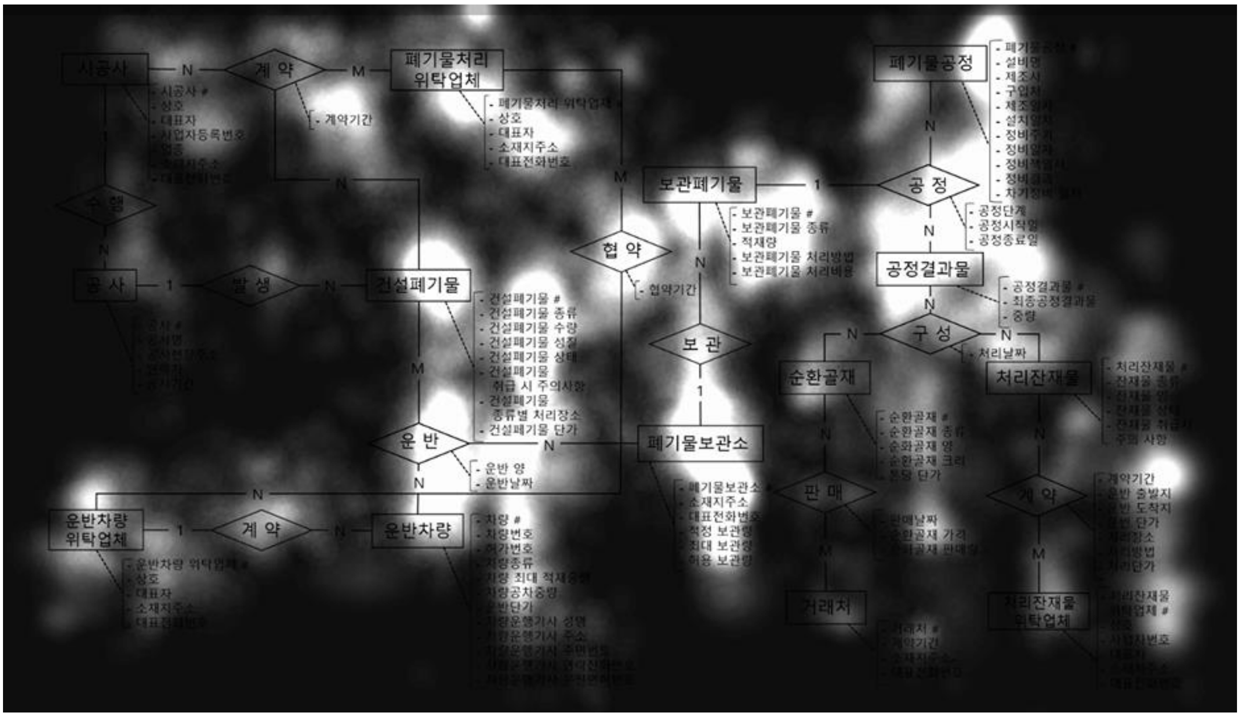
Bold lettering: Keyword in text categorization
Parenthesis: Behavior of participant
Every script was originally written in Korean and then translated in English.

Appendix B

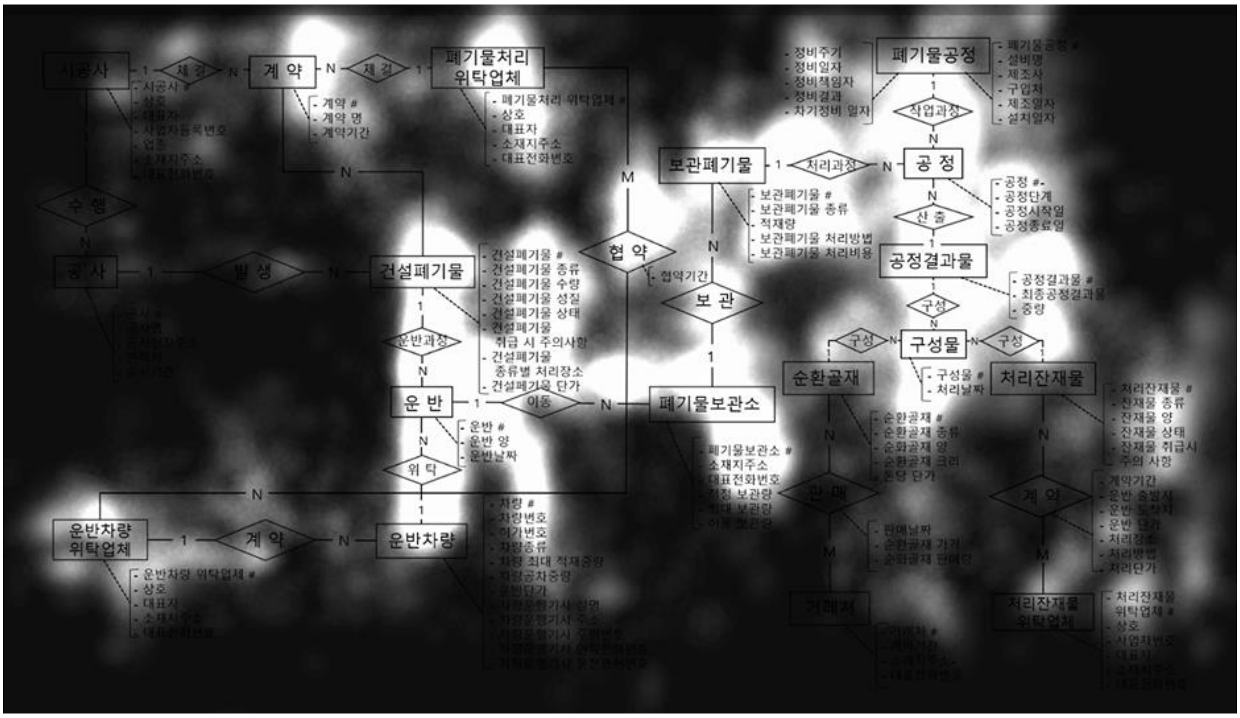
Glossary of Eye Tracking Technique

Gaze	An eye tracking metric, usually the sum of all fixation durations within a prescribed area. Also called "dwell", "fixation cluster", or "fixation cycle".
Fixation	The moment when the eyes are relatively stationary, taking in or "encoding" information. Fixations last for 218 milliseconds on average, with a range of 66 to 416 milliseconds.
Saccade	An eye movement occurring between fixations, typically lasting for 20 to 35 milliseconds. The purpose of most saccades is to move the eyes to the next viewing position. Visual processing is automatically suppressed during saccades to avoid blurring of the visual image.

Focus Map of Unfamiliar Domain (Waste Processing System)



[Figure B-1] Focus Map on Construct Overload Model in Unfamiliar Domain



[Figure B-2] Focus Map on No Construct Overload Model in Unfamiliar Domain

국문초록

컨스트럭트 오버로드가 진정으로 모델 퍼포먼스에 악영향을 미치는가?

–모델 전문가 중심의 실험 연구–

서 지 혜
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정보 시스템 개발에 있어서 주요 활동은 정보 시스템이 지원하고자 하는 영역의 개념 모델을 수립하는 일과 관련이 깊다. 이런 모델들은 정보 시스템 요건들을 명시하는데 필요한 기본 수단인 모델링 문법을 사용해 만들어진다. 하지만, 모델링 문법의 실제 활용은 잘 알려져 있지 않고 Construct Overload 같은 모델링 문법에 관한 몇몇 이슈들은 여전히 미해결 상태로 남아있다. 개념모델의 Construct Overload 관련하여, 과거의 연구들은 연구 방법 측면에서 몇 가지 부족한 점이 있었을 뿐만 아니라 심지어 같은 주제에 관해서 모순되고 상반된 결과들을 보였다.

본 논문에서, 우리는 Construct Overload 가 개념 모델 사용자들로 하여금 도메인을 더 효율적으로 이해할 수 있게 만들 수 있는지 여부를 시험하는 실험을 하였다. 또한 개념모델에서의 Construct Overload 를 더 완벽하고 정확하게 이해하기 위해, 우리 연구는 세가지 핵심 사항에 집중하였다. 이 세가지 사항은 모델링 문법 의미(Semantic)에 대한 평가, 연구 참가자, 그리고 도메인 친숙도(Domain Familiarity)이다. 즉, 본 연구는 Construct Overload 를 다양한 영역 친숙도(Domain Familiarity)에서 실험하여 실제 모델링 전문가들의 인지과정을 깊이 있게 조사했을 뿐만 아니라 실제적인 개념모델 사용에 초점을 맞춰서 연구를 진행함으로써 과거에 상반되는 연구 결과들에 관해서 합의점을 도출하였다. 본 연구는 개념 모델의 유용성을 넓힐 것이며 개념 모델을 생성 할 때 Construct Overload 를 포함여부를 안내하는 역할을 할 것이다.

키워드: 개념모델, 개념모델 문법, 컨스트럭트 오버로드, 도메인 친숙도, 도메인 지식, 정보시스템 개발

학번: 2011-30157