# USING INTERACTIVE DOMAIN OVERVIEWS TO DEVELOP DEEP UNDERSTANDING IN A COMPLEX REASONING TASK

by

Aaron John Dewald

A thesis submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Master of Science

Department of Educational Psychology

The University of Utah

December 2015

The University of Utah Graduate School

## STATEMENT OF THESIS APPROVAL

The thesis of **Aaron John Dewald**

has been approved by the following supervisory committee members:

**Kirsten Butcher**, Chair **4/30/15**
Date Approved

**Michael Gardner**, Member **4/30/15**
Date Approved

**Robert Zheng**, Member **4/30/15**
Date Approved

and by **Anne Cook**, Chair/Dean of

the Department/College/School of **Educational Psychology**

and by David B. Kieda, Dean of The Graduate School.

# ABSTRACT

Representations in the form of concept maps have been shown to be a benefit to leaners. However, previous research examined the influence of these representations in learning in well-structured environments. Additionally, previous research suggests that increasing the activity of students in learning environments has also been shown to yield gains in learning, called the generation effect. The current study extends the literature by examining the influence generative activities and concept map representations have on an ill-structured reasoning process, namely “thinking like a lawyer.” Pre- and posttests targeting factual knowledge, recall, and transfer were used to assess learning, while verbal protocols were implemented to examine learning processes used by participants. Results were mixed. Representation and activity had no effect on factual knowledge, recall, and near transfer measures. Verbal protocol results showed that students who studied with the concept map representation condition produced a higher proportion of deep utterances during problem solving when using static representations compared to those that generated their representation. The opposite was true for students in the text list condition. Those who generated their text list representation during study produced a higher proportion of deep utterances in problem solving when compared to those who studied with a static list. Thus, a careful consideration of topical materials and learning environments is necessary to determine whether or not concept maps and generation effects will encourage deeper comprehension in learners.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

# CHAPTER 1

# INTRODUCTION

Law is a complex and challenging topic. Learning law requires the learner to not only encode legal terms, statutes, and laws for later recall, but to also apply this information within skillful legal analysis. Generally speaking, legal analysis can be broken down into five primary steps: (1) finding the issue, (2) recalling the applicable rule, (3) identifying facts that are relevant to the rule, (4) applying the rule to the fact pattern, and (5) deciding the outcome of the case (D. Threedy, personal communication, October, 2012). This process is often called “thinking like a lawyer” (Schwartz, 2001). Much of this process is facilitated through the casebook method.

The casebook method can be broken down into two pieces: the cases and the Socratic method. The cases are heavily edited judicial opinions or appeals that best illustrate a particular area of law. These cases then form the basis for discussion during the class. The discussion method typically used is the Socratic method.

In law, the Socratic method is a common methodology by which the professor seeks to increase student comprehension though interactive discourse. Essentially, a professor begins with a certain fact pattern, called a hypothetical, or hypo for short. This hypo will be similar to cases the students have read as assigned by the professor. The professor will ask a student repeated questions about the hypo until a contradiction becomes apparent. The professor then uses the contradiction to facilitate critical thinking (i.e., thinking like a lawyer) and idea generation by focusing on ambiguity, assumptions, and faulty reasoning. Law professors expect that students will be able to transfer these skills to other topics in the law domain.

## Thinking Like a Lawyer

It is a common misperception among law students that they simply need to memorize rules and statutes to succeed in law school (D. Threedy, personal communication, October, 2012). Law students tend to follow typical patterns of study; like students in other domains, they tend to equate learning to memorizing facts or recognizing main points from learning materials (Schwartz, 2001). Because “thinking like a lawyer” requires application of knowledge to novel contexts and an ability to transfer knowledge across multiple situations, students must develop robust, flexible knowledge structures to ultimately succeed in law school. However, students’ focus on memorization and recall results in the development of rote, inflexible structures of knowledge. As a result, the typical student’s learning processes leave him or her ill-prepared for success in law school.

In order to understand when and how different learning processes lead to different knowledge outcomes, a distinction needs to be made between remembering new material and learning deeply from it (Kintsch, 1994). Rote knowledge has been described as "inert ideas,” in that these ideas can be recalled, but cannot be used or applied to new situations (Whitehead, 1929). Rote learning results from repetitive study and processes that emphasize encoding (but not integration or transformation) of incoming information.

Rote learning typically results in a shallow understanding of the learning materials, such that learners can reproduce, recall, or recognize the learned information, but cannot transform or apply it (Kintsch, 1994; Lambiotte & Dansereau, 1992; Novak, 2002). Though rote learning can be effective in some contexts (e.g., learning multiplication tables) and is a necessary precursor to deeper types of understanding, material learned through rote methods has limited potential for future use. For example, imagine a learner who memorizes multiplication tables, then is asked to solve a word problem in which multiple groups of a particular object need to be summed. A student who has a shallow understanding of the computational operations inherent in the multiplication table likely will not recognize the appropriateness of multiplication for solving the novel problem.

In order for a student to learn, he or she needs to deeply comprehend the learning material. Deep comprehension in a learning domain results in a flexible, reusable mental model that can be used outside the context in which it was learned (Kintsch, 1994). This allows learners to approach unique and novel problems and apply their knowledge in a meaningful way. Deep comprehension occurs when connections are made to prior knowledge and students integrate the to-be-learned information with prior knowledge. As a result, students can make inferences and transfer this newly acquired knowledge to different learning contexts. Deep comprehension results in learners being able to go beyond the surface features of learning materials and draw connections between the underlying concepts (Chi, Feltovich, & Glaser, 1981).

To better delineate differences between shallow and deep comprehension, we can look to models that inform our understanding of integration and transfer. Because deep comprehension requires integration of new and prior knowledge, learners must possess pre-existing, relevant knowledge structures and categories (Chi et al., 1981). One way to support deep comprehension may be to promote well-developed, organized knowledge structures into which new information can be integrated.

## Construction-Integration Model

A well-known model of comprehension, introduced in 1983, is the Construction-Integration (CI) model (Kintsch, 1988; van Dijk & Kintsch, 1983). The CI model originally targeted learning from printed text materials. However, Butcher and Kintsch (2012) argued that many of the same comprehension rules apply when using hypertext or online multimedia. The CI model consists of two key processes: knowledge construction and knowledge integration (Wharton & Kintsch, 1991).

Text comprehension starts with the construction of a loosely-built, temporary, node-based mental framework based on the information conveyed by the text. The mental framework is known as a proposition network or textbase (Kintsch, 1994; Wharton & Kintsch, 1991). When the proposition network is combined with the learner's prior knowledge, an elaborated propositional network is formed (Wharton & Kintsch, 1991). One of the main drivers of this construction process is a learner's prior knowledge – the primacy of prior knowledge in this model is consistent with many studies that have shown the importance of prior knowledge in comprehension (Kintsch, 2008; Schwartz & Bransford, 1998). The network consists of nodes (as propositions) and connections. Nodes are interconnected and individual scores of connection strength are associated with each interconnection (Kintsch, 1988).

The integration process is one by which relationships in the mental framework are strengthened, weakened, or removed through an activation process (Kintsch, 1988). The integration process utilizes the proposition network created in the construction process and "fine tunes" the connections between nodes, removing weak connections and stabilizing positive ones (Kintsch, 1988; Wharton & Kintsch, 1991). This process is highly context-sensitive; that is, the context of the text materials allows the learner to prune his or her associative net to relevant nodes and their connections through a "sense-elaboration" phase (Kintsch, 1988).

Three levels of representation of varying complexity can best represent the proposition network that is created in the CI model. These three levels, the surface, textbase, and situation model representations, describe the proposition network at varying depths (Kintsch, 1983).

The surface level representation is the most basic representation level of knowledge that can be formed. The surface level representation enables verbatim, word-for-word recall (i.e., exact memorization) of the learning materials. A surface level representation can be formed successfully even with little to no understanding of text meaning, only retention of the words themselves. Though some students rely on direct, word-for-word memorization of information relevant to learning (e.g., law students who memorize the exact phrasing of statutes and restatements), more frequently, students are trying to develop a textbase representation of knowledge (Butcher & Kintsch, 2012). A textbase representation differs from the surface level representation in that it does not include an exact representation of the learning materials. Instead, the learner constructs a propositional model of the text content that is a faithful representation of the text’s content, but at a more abstracted level (Kintsch, 1994). Students who attempt to "memorize" learning materials typically are focused on remembering the main ideas of the text rather than being able to reproduce its exact format (Butcher & Kintsch, 2012). Students who have formed a textbase level of comprehension usually can paraphrase the materials, but cannot apply or transfer their knowledge to new contexts or situations. From a practical perspective, a textbase level of knowledge supports students' performance on assessments that require recognition or restatement of learned materials (e.g., selecting correct definitions from a multiple-choice list or restating basic ideas from the learned materials).

The third level of knowledge representation described in the CI model is called the situation model. The situation model exemplifies deep learning (Kintsch, 1994). A hallmark characteristic of the situation model network is that it is a more elaborated, more flexible representation than either the surface level or the textbase representations. The situation model is created when learners integrate the incoming text information with their prior knowledge to develop an organized and elaborated propositional network (Kintsch, 1994). A well-formed situation model facilitates synthesis, inference, and transfer and allows learners to apply their knowledge to problems or situations outside of the original, learned context.

## Novices vs. Experts

Many students enter a learning environment as a novice, and therefore have a limited prior knowledge of the domain in which to integrate newly acquired information. A novice's knowledge structure within a new domain is often ill-formed and incomplete. As a result, these students often employ strategies, such as encoding and means-ends analysis, that are consistent with the creation of a textbase level of representation (Chi & Glaser, 1985; Chi, Glaser, & Rees, 1982; Kalyuga, Ayres, Chandler, & Sweller, 2003). Additionally, novices tend to focus on surface features of a problem set (Chi et al., 1981). Chi et al. (1981) examined the differences in the ways that experts and novices in physics used their knowledge in problem-solving tasks. They found that, unlike experts, novice learners categorized problems on surface features rather than the underpinning, deeper physics concepts.

In order for novices to move toward expert understanding as they learn in a domain, they need to develop a more elaborate and organized knowledge framework that approximates that of an expert. Experts display robust frameworks, extensive prior knowledge, and qualitative experience that they enable when encountering novel problems in a domain (Chi & Glaser, 1985; Chi et al., 1982; Chi et al., 1981). Experts can efficiently integrate incoming information and, therefore, can work more effectively with learning materials (Kalyuga et al., 2003). In order to facilitate the transition from novice to expert, learners need materials and interactions that will engage them deeply with the content and facilitate the development of a well-organized knowledge framework.

## Concept Maps to Scaffold Cognitive Processing

One way in which the development of a well-organized knowledge framework may be supported in novices is by using concept maps. Concept maps are two-dimensional, spatial-semantic representations of concepts and their relationships, which are depicted via nodes and links (Gurlitt & Renkl, 2010). In a concept map, concepts are depicted via nodes that usually contain text information. Relationships between concepts are represented by links between the nodes. These relationships may be labeled with one or more words that describe the relationship being depicted. Novak and Gowin (1984) describe concept maps as a group of concepts linked with a word to form a proposition. For example, the sentence "ball is round" would yield two concepts, "ball" and "round," connected by the word "is." This forms a simple, yet meaningful, relationship between "ball" and "round" and is a simple proposition that could be found in a concept map. An example of this concept map can be seen in Figure 1.

Concept maps can help learners by scaffolding and supporting cognitive processing, better articulating relationships between complex ideas, and providing multiple retrieval paths for accessing knowledge (O'Donnell, Dansereau, & Hall, 2002). Concept maps can make central ideas of a learned topic more salient; that is, they facilitate understanding of the macrostructure of a topic (Chmielewski & Dansereau, 1998). Research has shown that learners who study with concept maps can recall more central ideas of a topic than those who study with text (Adesope & Nesbit, 2013).

Hall and O'Donnell (1996) compared the use of concept maps as study materials with traditional text materials. The experimental group studied information about the human central nervous system through the use of concept maps; the control group studied the same information presented as a passage of text. Both the map and the text contained the same number of words. Hall and O'Donnell's results showed that learners in the concept map condition produced more macrostructure concepts during a free-recall task than those who used the text-only materials.

Chmielewski and Dansereau (1998) tested the efficacy of concept maps in learning and retention. First, they trained students on concept maps using three tasks:

students first were provided with an overview of concept map features, students then were asked to create their own, and finally, students were asked to judge fellow participants' self-generated concept maps. On a later day, students were asked to study two separate topics presented as text. Results showed that students who were in the concept map condition were able to remember more macrolevel concepts during a free-recall task than those who were not. These results are largely consistent with Hall and O'Donnell's (1996) results, except that these students did not study with a provided concept map. Thus, studying provided maps and generating new concept maps may lead students to identify and encode a macrostructure organization described in a text.

Concept maps may be particularly useful for domain novices, as research has shown that students with low verbal ability or low prior knowledge benefit the most from the use of concept maps (O'Donnell et al., 2002). Research by Lambiotte and Dansereau (1992) studied the effect of concept maps in a biology context. They examined the effects of three different types of information presentations on student learning: concept maps vs. hierarchical text outlines vs. text-based bullet lists. For learners with low prior knowledge, maps were found to be superior to the other two types of presentations. The maps had the effect of an advance organizer for the students with low prior knowledge, providing structure in an otherwise unfamiliar topic. When learners have low prior knowledge, concept maps appear to serve as a tool to scaffold knowledge and assist learners in developing a more well-developed knowledge structure by providing them with relationships and connections they may not see in text-only learning materials.

Concept maps also are useful in that they allow a learner to make explicit his or her current knowledge about a topic through creation of a concept map (Novak & Gowin, 1984). The process of a learner creating a concept map provides the learner with an external, workable approximation of his or her cognitive structure. This gives both teachers and learners an ability to identify weaknesses, strengths, and misinterpretations in a learner's mental model of the concept. The exercise of creating a concept map can also be a learning experience. Through the process of creating the concept map, learners may recognize new relationships between concepts they had not otherwise considered and create additional propositions to depict those relationships. One question is whether it is the act of generating content itself or the format of the generated content that is driving the majority of the benefits. As discussed in the next section, a great deal of research has shown strong benefits for learners when they generate materials (in a variety of forms) during study.

## The Generation Effect

A well-known finding in the learning sciences is that information is better remembered when generated rather than read by a learner (Slamecka & Graf, 1978). This effect, called the generation effect, refers to the principle that there is benefit in learning through active measures – that is, learning through activity is superior to learning passively (Chi, 2009).

The generation effect has undergone extensive research over the last 30 years (Chi, 2009; Chularut & DeBacker, 2004; Jacoby, 1978; Slamecka & Graf, 1978). For example, Slamecka and Graf (1978) tested the generative effect by using a controlled paired-associate test. They provided participants with a target word accompanied by the first letter of an associate word. Participants were asked to generate the first word that came to mind using the first letter as a cue. Additionally, some paired associates were complete, asking the participants only to read the word pairs. Slamecka and Graf's research found that words that were generated were better recognized, and were recognized with more confidence, compared to words that were simply read during study.

The benefits of the generation effect have also been explored in the domain of concept maps. Chularut and DeBacker (2004) explored the effect of concept maps as an English as a Second Language learning aid. Learners were asked to read a text passage, then either to discuss the main ideas of the text or to create a concept map using the main ideas from the text. Chularut and DeBacker found that learners who were asked to generate a concept map outperformed learners who simply discussed a text.

These results suggest that generating concept maps can result in similar benefits to generating other types of materials. However, one question is the extent to which novice learners can generate accurate and meaningful representations, especially when learning materials may be complex or span multiple documents or sources. Whereas the above studies have mainly examined the generation of maps from a single text, a core question is whether learners can successfully generate maps from more difficult materials, especially when those materials are comprised of multiple examples that must be integrated and synthesized. Further, it is unclear as to whether or not novice learners can successfully generate accurate materials when learning in a complex domain. In these instances, novices may need assistance to guide them toward a more accurate representation. How much or how little we assist learners in their learning can be described with the concept of the assistance dilemma.

## Assistance Dilemma

The assistance dilemma (Koedinger & Aleven, 2007) refers to the problem of balancing the amount of assistance given or withheld during the course of learning. Koedinger and Aleven (2007) explored the assistance dilemma through the use of a computerized cognitive tutor. A cognitive tutor provides a computer-based learning environment in which the system can provide dynamic feedback to the learner. This can mimic the type of feedback a human tutor might provide a learner. The cognitive tutor provides two means of assistance to learners as they work on their problems. First, students are given feedback when an error is found in their work. The feedback is aimed at explaining why their submitted answers are incorrect. Second, students are able to ask the system for hints. The hints are provided at multiple levels and are aimed at assisting the learner take the next step for solving the problem. These two means of assistance are aimed at balancing the amount of information generated by the students and the amount given as assistance. Studies that examined the effectiveness of the Cognitive Tutor tutor in fields such as geometry (Anderson, Corbett, Koedinger, & Pelletier 1995), LISP programming (Anderson et al., 1995), and algebra (Koedinger, Anderson, Hadley, & Mark 1997) have found a significant, positive effect for the tutor when compared to standard learning environments.

The assistance dilemma has also been explored with concept maps. Chang, Sung, and Chen (2002) explored the impact of assistance in the generation of concept maps on enhancing text comprehension in elementary students in various science topics. In the Chang et al. study, learners began by reading and studying relevant articles from scientific and social science domains. Students were then placed into one of four conditions. In one condition, the learners were asked to construct a concept map based on the studied articles. Two conditions were semistructured, assisted conditions that involved students working with partially completed concept maps. In one, the maps were complete but partially incorrect. In this final condition, learners had to correct the erroneous map by removing or replacing nodes. In the other assisted condition, learners were provided concept maps that were correct, but only partially complete – requiring students to fill in the missing nodes and relationships. In both assisted conditions, learners identify which nodes were incorrect or missing based on their knowledge of the studied articles. The final condition was a control condition where students only studied the articles. They found that students who were in the assisted conditions performed significantly better in posttest comprehension outcomes when compared to students who were asked to create a map with no assistance or the control group of text-only materials. This finding supports the notion that some form of assistance during the course of generating and learning from concept maps can lead to better outcomes than those that provide no such assistance.

The finding that assistance in generating a concept map facilitates optimal learning is not completely consistent with results from Hauser et al. (2006). Like Chang et al. (2002), Hauser et al. (2006) examined the impact of assistance on concept map generation. In the Hauser et al. research, students began by studying a complex text on the topic of ethical and biological issues in human embryo research. Students were then placed into one of five conditions. In one condition, learners generated a map "from scratch" and were provided with no assistance. Two conditions were semistructured, assisted conditions with concepts-provided or concepts-arranged. In the concepts-provided condition, participants had assistance through a partially completed map that had concepts (nodes) provided. The participants were asked to spatially arrange the concepts and draw and label the links between the concepts. In the concepts-arranged condition, participants were provided assistance in that concepts (nodes) were already spatially arranged and the participants only drew and labeled links between the concepts. Students in the fourth experimental condition were provided with a completely worked out map that involved no generation. The final condition was a control condition where students did not work with a concept map after study. The Hauser et al. results showed that the "from scratch" map generation condition and the map-provided condition resulted in superior factual and comprehension outcomes than either of the two assisted conditions.

A key question is how the discrepancy between Hauser et al. (2006) and Chang et al. (2002) can be reconciled. Two primary differences between these studies were the participants and the topic being studied. Hauser et al. utilized college-aged students studying a biological/ethical domain. Chang et al. studied fifth-grade students in science domains. It might be presumed that college-aged students are more mature learners and, therefore, might be more able to understand how to fully generate and utilize concept maps. The topic of Hauser et al. was more abstract without clear-cut answers. Additionally, one could argue that these older students could be more familiar with ethical problems due to their life experiences. Chang et al. used very novice learners who might not be fully able to understand how to create a concept map from scratch, therefore requiring more assistance with their use. Further, their topic was very conceptually concrete and well defined. Although one might assume that the conclusion should be that older learners do not need assistance in learning from concept maps, it is also possible that these studies show that learners who are generating new or unfamiliar representations benefit from assistance. In a domain such as law, where students are creating abstracted representations from multiple, difficult texts, it is an open question whether or not they require assistance to do so successfully.

Taken together, prior research is unclear on whether or not to provide assistance and to what level the assistance is provided. It may depend on the type of learner, the topic being studied, and the overall objectives for the instruction. The ultimate challenge to find a prudent balance between asking learners to generate all information from scratch (i.e., Generation Effect), or be assisted with some information (i.e., Assistance Dilemma) remains.

## Assessing Cognitive Processing via Self-explanation

In order to better understand when and how students may benefit from different levels of assistance during study, assessments are needed to measure not only students' resulting knowledge, but also the cognitive processes in which they engage during learning. Assessing these processes also provides a sensitive measure to analyze students' changing understanding across a learning event.

According to Chi, Bassok, Lewis, Reimann, and Glaser (1989), the most direct way to assess understanding is to, "examine the explicit explanations that students provide while studying it" (p. 151). By directly analyzing the explanations provided by the student, insight into their overall understanding of the topic can be obtained. These explanations by students are gathered through a methodology called self-explanation.

Self-explanation is a technique by which learners explain how they understand the learning materials out loud as they study (Chi et al., 1989; Chi et al., 1994; Renkl, 1997; Roy & Chi, 2005). This technique engages learners in a more active learning experience and allows learners, as well as researchers who analyze the content of students' self-explanations, the ability to monitor their progressive understanding (Roy & Chi, 2005). Self-explanation is deliberate and involves the conscious control of the learner (DeLeew & Chi, 2003). This technique is often used to facilitate deeper understanding of the learning materials by allowing learners to externalize the cognitive processes induced by the learning materials; that is, by asking students to say what they are thinking, researchers are allowed a view into the cognitive processes of a student (Chi et al., 1989). A high-quality self-explanation will often take the form of an inference activity. When self-explanation is successful, a learner will often create inferences from ideas not explicitly stated in the learning materials. Additionally, self-explanation can facilitate the integration of to-be-learned information with the student's prior knowledge, if he or she makes these connections. Prior knowledge activation is one of the key processes in deeper learning outcomes (Chi et al., 1994), but not a prerequisite for high-quality self-explanations (Renkl, 1997).

Research has shown positive benefits from engaging in self-explanation during learning. Chi et al. (1989) asked students to talk aloud while studying physics materials and answering problem-solving assessment questions. They found that those students who spoke more during studying and problem-solving performed better and were considered "good." Further, after analyzing these "good" vocalizations, they found these students had more inferences; better self-assessment of their knowledge; and richer, deeper utterances than those students who were considered “poor” vocalizations. These types of utterances by “good” students came to be known as self-explanations.

Fortunately, self-explanation is not something that only good students are able to do (although, only “good” students may do so spontaneously). Self-explanation can be elicited from students through the use of prompts. Chi et al. (1994) compared the effects of prompts encouraging learners to self explain. Students read a heart and circulatory system text sentence by sentence. After reading each sentence, students were prompted to explain the meaning of individual sentences of a text. Students in the no prompt condition were given no such prompts and simply read the text. It was found that students who were prompted significantly outperformed students in the no prompt condition. Further, students significantly outperformed those in the control condition on more difficult questions, such as those that required the student to make inferences.

Benefits of self-explanation are not limited to situations in which students work with text-only representations. Research by Ainsworth and Loizou (2003) explored the effect of self-explanations while working with other types of media. Twenty subjects were separated into two groups: text only and diagrams. Both groups utilized materials from the heart and circulatory system, and both groups self-explained while studying these materials. Results from posttest analysis showed those who self-explained more performed better in posttests – consistent with previous research. Students in the diagram condition produced significantly more self-explanations than those in the text-only group. This indicates that using visual representations, such as diagrams, can help elicit better self-explanations by students, thereby facilitating deeper comprehension and a more robust knowledge structure.

Though self-explanation techniques have shown to provide learners with a better understanding of the material, they also can be beneficial to researchers in that they externalize the thinking processes of the learner. By transcribing, segmenting, and coding the self-explanations produced by a learner, the researcher can identify and compare the cognitive processes implemented by a student (Chi, 1997).

## Research Questions

This study explored the effectiveness of concept maps as tools for deep comprehension of multimedia learning materials in legal education. Specifically, this study examined whether or not students' learning from text and videos about legal topics could be improved via study of concept maps compared to text only materials. This research study extended beyond previous studies of concept maps in that it explored the impact of using a computer interface to facilitate learner interaction with concept maps as they learned a complex topic using video instruction. Thus, the current research examined whether computer-supported generation can increase the potential impact of concept maps as a learning tool. It was expected that students who were asked to take part in creating their learning materials, with the benefit of feedback, would develop deeper, more well-structured knowledge representations than those who did not. Therefore, the primary research questions were as follows:

1. To what extent does a domain overview facilitate deeper understanding in a complex reasoning task?
2. Does generation of a concept map representation, with assistance, enhance its utility?

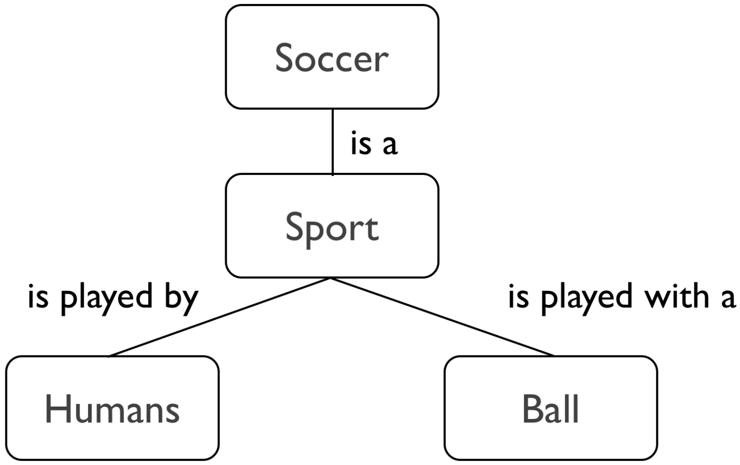


*Figure 1***.** Example of a concept map.

# CHAPTER 2

# METHODS AND PROCEDURE

## Participants

Participants were recruited from four ABA accredited law schools in the United States. A liaison from each of the schools was required for IRB approval. All participants were recruited via an email that was sent out from the liaison. A total of 60 students were recruited for the study (29 female, 30 male, 1 no reply; age: $M$ = 29 years.) Participants were compensated $30 for their participation.

## Design

A 2 (representation type) x 2 (activity type) design was used. Representation type varied the format of representation used during study: a spatial-semantic representation (see Figure 2) vs. a text list representation (see Figure 3). Activity type varied the degree to which user interaction was necessary to develop the representation used during study: the representation was either system-provided or user-generated. Four experimental conditions were examined: user-generated spatial-semantic representation ($n$=16), system-provided spatial-semantic representation ($n$=15), user-generated text list representation ($n$=14), and system-provided text list representation ($n$=15). All participants were randomly assigned to one of four experimental conditions.

## Materials

Participants were presented with four different sets of materials during the course of this study: a demographic survey, self-explanation training materials, instructional videos, and study materials as appropriate to each of the experimental conditions. All materials were delivered through a Safari web browser on a 15" 2014 MacBook Pro.

### Demographic survey

The demographic survey consisted of six questions that described the characteristics of the participant (e.g., gender, age, year in school) and their comfort using various study strategies by self-rating on a scale of 1 (never) to 10 (always) (e.g., "[I] write a summary of what I learned").

### Self-explanation training materials

The self-explanation training materials consisted of an instructional video that demonstrated optimal self-explanation during study. The video provided participants with a definition and overview of self-explanations, provided three tips that lead to effective self-explanations (e.g., "Avoid describing what you see"), and provided examples and nonexamples of effective self-explanations. The self-explanation training video was 6 minutes and 21 seconds long.

### Instructional videos

The instructional videos presented basic concepts about the statute of frauds, which is a subtopic of contract law. The videos outlined the basic structure of a statute of frauds issue, walked the viewers through an example, and covered four common exceptions found in statute of frauds issues.

The instructional videos were embedded on a web page. Controls, such as pause, stop, and fast-forward, were not provided in order to ensure that presentation time was consistent for all participants. The average video length was 389 seconds (6 minutes 29 seconds) in length, with a standard deviation of 142 seconds (2 minutes 22 seconds).

## Study materials

The study materials consisted of four different representations of statute of frauds information that varied as appropriate to each of the four experimental conditions. Each representation consisted of seven nodes or sentences arranged according to their representation. User-generated study materials also contained seven distractor nodes used to discourage a trial-and-error study method. A subject matter expert in the domain of law provided the text and visual representations that were adapted for use in a computer-based environment.

### System-provided text list interface

This interface utilized a text-only list of meaningful questions necessary to reason effectively about statute of frauds cases (see Figure 3). In this interface, the system provided students with a full, numbered list for study.

User-generated, text list interface

This interface used the same list of text questions as the system-provided text list interface, but also included the seven distractor statements to increase the complexity of the task and discourage simple guessing strategies. Instead of providing a static, system-provided representation, this interface provided a drag-and-drop tool that enabled the generation of a numbered list of questions (see Figure 4). Feedback was provided in that correct node placements "snapped" into place whereas incorrect placements reverted back to their original location.

System-provided spatial-semantic interface

The spatial-semantic representation provided a visually organized map of the same statute of frauds questions as in the text-only list. The spatial-semantic organization provided each question in a node, with spatial organization showing the order and relationships between questions (see Figure 2). Functionally, this visual organization of questions and statements created a decision tree that could be used to analyze and work through statute of frauds problems. In this interface, a complete (system-provided) map was provided by the system.

User-generated spatial-semantic interface

This interface utilized drag-and-drop interactions to create the spatial-semantic representation. As seen in Figure 5, nodes were provided at the bottom of the interface and the visual organization of the map was indicated in the main area of the interface. Nodes were dragged and dropped to specific locations in the interface in order to generate the full representation. Feedback was provided in that correct node placements “snapped” into place on the map, while incorrect placements reverted back to their original location (see Figure 5 for a screenshot.)

## Assessments

### Pretest materials

The pretest was a two-part, 11-question assessment. All scores were calculated as a proportion correct.

#### Factual knowledge

The first part of the pretest materials were 10 questions that tested factual knowledge. Factual knowledge questions were eight multiple-choice, and two multiple-select questions that assessed a participant’s factual knowledge of the domain. For example, “How many types of transactions are covered by the statute of frauds?” Each multiple choice and true/false question was worth one point. In the case of multiple-select questions, one point was given for each correct answer selected and one point was given for each incorrect answer not selected. Answers were automatically scored by a computer system. Overall, factual knowledge questions had a maximum score of 18 points

#### Near transfer

The second part of the pretest assessment was one short-answer, near transfer question. The near transfer question was based in the contracts domain and involved the statute of frauds. It required participants to apply their knowledge about the Statue of

Frauds to infer answers/implications in novel contexts. Answers were scored by the researchers using a four parameter, three level rubric. Partial credit was given for partially correct answers. Overall, the near transfer question had a maximum score of 12 points.

## Posttest materials

The posttest was a three-part, 26-question assessment. All scores were calculated as a proportion correct.

### Factual knowledge

The first part of the posttest consisted of the same 10 questions that were given during the pretest.

### Recall

The second part of the posttest materials were 10 recall questions. Recall questions asked students to recognize information that was explicitly conveyed in the learning materials. These questions were three multiple-choice, two multiple-select, and five true/false questions. Each correct answer was worth one point. In the case of multiple-select questions, there was a possibility the participant could score more than one point. One point was given for each correct answer selected, and one point was given for each incorrect answer not selected. Answers were automatically scored by a computer system. Overall, recall items had a maximum combined score of 18 points.

Near transfer

The final part of the posttest assessment was five near transfer questions. The near transfer question from the pretest materials was repeated at posttest. The other four questions consisted of alternate scenarios in which the participant had to apply their knowledge to novel hypotheticals. For example, one near transfer task asked participants to solve a problem in which the sale of *real property* was involved. This contrasts with examples given in the instructional videos that provided a worked example that involved analyzing statute of frauds issues in a sale of goods valued over $5000. Another example near transfer item required participants to evaluate and critique a response to a hypothetical by an imagined peer. By asking learners to "explain what's wrong" with a response, learners attempt to transfer and apply their knowledge more robustly in a novel context. These questions were short answer style and graded by the researchers using a four parameter, three level rubric. Partial credit was given for partially correct answers. The maximum score on these questions was 59 points.

## Verbal Analysis

The participants' verbal utterances were captured with an Apple Macintosh laptop running the Screenflow application and later transcribed by a professional transcription service.

The transcripts were segmented into complex propositions (Kintch, 1988) approximately equivalent to an idea unit called an utterance (see Table 1). Following segmentation, each utterance was assigned a code as described below.

# Coding Rubric

The coding rubric consisted of 26 codes in four different categories. Each category corresponded to a cognitive process that could be observed during learning (deep processing, shallow processing, metacognitive processing, and other.) Major categories are described below. For examples of categories and codes, please see Appendix A.

## Deep processing

An utterance was coded in the deep processing category if it demonstrated a high-level comprehension process associated with situation model development. High-level processes occurred when individuals generated new content or transform provided information; these processes included integration, inference, elaboration, application, and analysis.

## Shallow processing

An utterance was coded in the shallow processing category if it demonstrated a low-level comprehension process that is associated with textbase development. Low-level processes occurred when individuals did not go beyond the original meaning given content; these processes include reading and paraphrasing.

## Metacognitive processing

An utterance was coded in the metacognitive processing category if it indicated monitoring or planning of their own learning and problem-solving processes.

Metacognitive processes occurred when a learner expressed doubt about their knowledge (negative), expressed awareness of their comprehension (positive), or expressed strategic thinking while approaching a problem (planning.)

## Procedure

This experiment was conducted at participating law schools, with each participant seated in front of a laptop computer and wearing headphones that had a built-in microphone. All on-screen interactions and verbal utterances were captured. The experiment took place in study rooms that were made as equivalent as possible (lighting, work space, noise, etc.) The experiment took approximately 100 minutes ($M$ = 98.25, $SD$= 7.04) to complete. Participants were run one at a time. Informed consent was obtained prior to participation in the study.

To begin the study, a demographic survey was administered. Participants were given 5 minutes to complete the demographic survey.

Next, participants were given 15 minutes to complete the pretest assessment that measured their prior knowledge of the statute of frauds topic with 10 factual knowledge questions and one near transfer question. Participants were told to try their best to answer the questions.

Following the pretest assessment, participants viewed the self-explanation training video. At the conclusion of the video, there were two examples with prompts that asked the participant to articulate to the experimenter what made examples either good or bad based on what they had learned by viewing the training video. After this, the participant practiced self-explanation techniques under the guidance of the facilitator by talking through a simple word problem. The facilitator provided feedback to the participant to ensure the participant correctly executed self-explanation techniques.

After completion of the self-explanation training, participants watched three instructional videos. Participants viewed all the videos, one time in the order provided, before continuing with the experiment.

Upon completion of the instructional videos, participants studied with the representation appropriate to their experimental condition, then used the representation for problem-solving.

In the study phase, participants studied or interacted with their assigned interface for 5 minutes. Those in the user-generated conditions worked to build their representation (spatial-semantic map or text list) using the drag-and-drop described previously, while those in the system-provided conditions studied their spatial semantic map or text list. If participants in the user-generated conditions completed construction of their representation before time was up, they were asked to study what they had generated. In addition to generating or studying with their assigned interface, all participants self-explained (aloud) as they generated or studied. The facilitator prompted the participant with content-free prompts in the event there was more than 10 seconds of continuous silence from the participant. Some examples of the content free prompts implemented are, “Could you say more about that,” or “What are you thinking about?”

In the problem-solving phase, participants were asked to solve two statute of frauds problems of increasing difficulty. In addition to the problem text, participants were given representation that they had studied or generated (regardless of whether or not the representation was completed in the user-generated conditions). Participants again self-explained (aloud) as they solved both problems. Participants were given a maximum of 5 minutes to solve each problem, for a total of 10 minutes.

Upon completion of the problem-solving phase of the study, participants were asked to complete the posttest assessment.  Participants were given 40 minutes to complete the posttest.

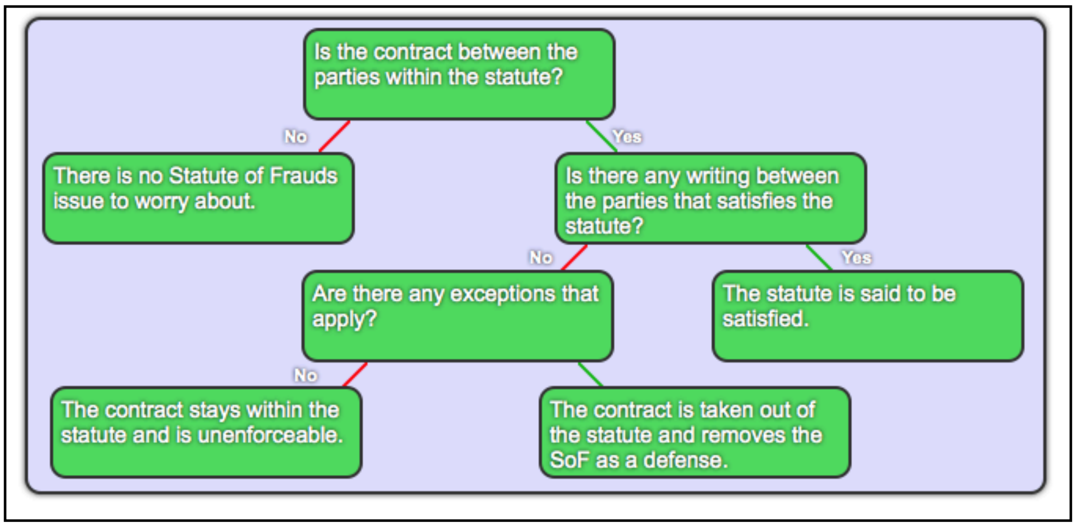


*Figure 2.* System-provided spatial-semantic interface.

1. Is the contract between the parties within the statute?
2. If not, then there is no statute of frauds issue to worry about.
3. If so, is there any writing between the parties that satisfies the statute?
4. If so, the statute is said to be satisfied.
5. If not, are there any exceptions that apply?
6. If so, the contract is taken out of the statute removes the SoF as a defense.
7. If not, the contract stays within the statute and is unenforceable.

*Figure 3***.** System-provided text list interface.

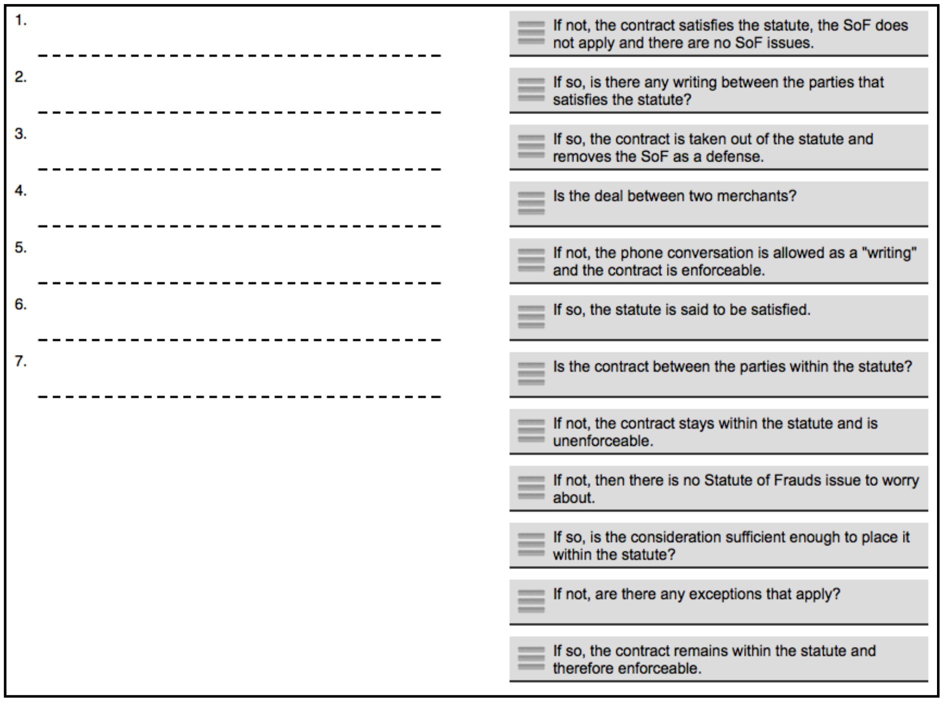


*Figure 4.* User-generated text list interface

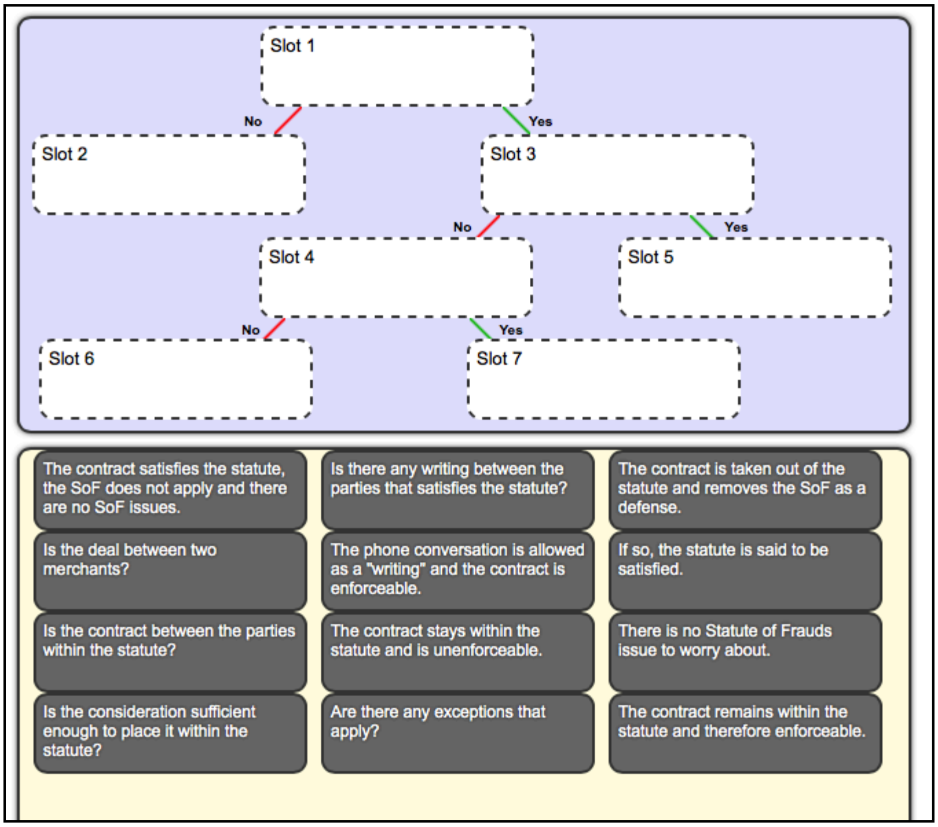


*Figure 5.* User-generated spatial-semantic interface.

Table 1

*Raw verbal transcript segmented into complex propositions (utterances)*

<table>
<tr><th>Raw transcript</th><th>Segmented Utterances</th></tr>
<tr><td rowspan="8">First I’m going to read the hypo. Ben and Jerry make an oral contract with Moo Juice under which Moo Juice will sell Ben and Jerry – so I’m going to draw a picture, um, just to keep everything straight. So Moo Juice and Ben and Jerry. Um, so Moo Juice is going to sell Ben and Jerry 500 gallons of that specially produced, so that’s important. That sounds like an exception possibly under the UCC. Um, Chocolate milk that is made of very finely ground Mayan cocoa beans and contains added milk fat and vitamin D.</td><td>First I’m going to read the hypo. //</td></tr>
<tr><td>Ben and Jerry make an oral contract with Moo Juice under which Moo Juice will sell Ben and Jerry – //</td></tr>
<tr><td>so I’m going to draw a picture, um, just to keep everything straight. //</td></tr>
<tr><td>So Moo Juice and Ben and Jerry. //</td></tr>
<tr><td>Um, so Moo Juice is going to sell Ben and Jerry 500 gallons of that specially produced, //</td></tr>
<tr><td>so that’s important. //</td></tr>
<tr><td>That sounds like an exception possibly under the UCC. //</td></tr>
<tr><td>Um, Chocolate milk that is made of very finely ground Mayan cocoa beans and contains added milk fat and vitamin D. //</td></tr>
</table>

# CHAPTER 3

# RESULTS

In all analyses, a standard alpha level of .05 was used.

## Outcomes

### Pretest performance

A multivariate analysis of variance (MANOVA) was conducted using activity and representation type as the independent variable. Dependent measures were the proportion correct on the factual knowledge assessment and near transfer questions. No significant multivariate effects were found for activity or representation ($Fs < 1$). There was not a significant interaction between activity and representation ($F < 1$). Means and standard deviations are shown in Table 2.

### Posttest performance

A MANOVA was conducted using activity and representation type as the independent variables. Dependent measures were the proportion correct on the factual knowledge assessment, recall assessment, and the near transfer assessment. No significant multivariate effects were found for activity or representation ($Fs < 1$). There was not a significant interaction between activity and representation ($F < 1$). Means and standard deviations on posttest assessments are shown in Table 2.

## Processes

### Total number of system moves

A one-way analysis of variance (ANOVA) was conducted to examine whether or not the representation type factor (spatial semantic map vs. text list) influenced the total number of system moves made by participants during study in the generative conditions. In the generative conditions, each instance of a drag-and-drop behavior was coded as a "system move" regardless of whether or not the move was correct. No significant main effect of representation ($F < 1$) was identified. Means and standard deviations for the representation types are shown in Table 3.

### Proportion of correct system moves

A one-way ANOVA was conducted to examine whether representation type influenced the proportion of correct system moves made by a participant during study. A significant main effect of representation was found ($F_{(1,28)} = 5.38$, $p < .05$; $\eta^2_p = .15$). Participants who worked with the spatial-semantic representation had a greater proportion of correct moves than participants who worked with the text list representation (see Table 4).

### Completeness of representation

A one-way ANOVA was conducted to examine whether representation type influenced the overall completeness (measured as a proportion) of the representation generated by the participant during study. A significant main effect of representation was found ($F_{(1,28)} = 5.11$, $p < .05$; $\eta^2_p = .17$). Participants who generated the spatial-semantic representation had a more complete representation during problem solving than participants who generated the text list representation (see Table 5.)

## Learning Processes

In analyzing the verbal process data, 2 participants were removed from the analysis due to equipment failure.

### Total utterances

A two-way ANOVA was conducted to examine whether the total number of utterances made by a participant during problem solving was influenced by representation type or activity. As seen in Table 6, there was a significant main effect of activity ($F_{(1,54)} = 5.71$, $p < .05$; $\eta^2_p = .10$). Participants in the system-provided conditions made more total utterances than those in the user-generated conditions (see Figure 6). There was not a significant main effect of representation ($F < 1$). There was not a significant interaction between activity and representation ($F < 1$).

### Code Categories

A MANOVA (see Table 7) was conducted with activity and representation type as the independent variables and utterances in the deep, shallow, and metacognitive code categories as the dependent variables. Multivariate results demonstrated significant main effects of representation ($F_{(1,52)} = 3.05$; $p < .05$; $\eta^2_p = .15$) and activity ($F_{(1,52)} = 2.78$; $p$

=.05; $\eta^2_p = .14$), as well as a significant interaction between representation type and activity ($F_{(1,52)} = 3.10$; $p < .05$; $\eta^2_p = .20$). The univariate analyses are described below.

<u>Deep utterances</u>

There were no significant main effects of activity or representation (*Fs* < 1) on the number of deep utterances produced by participants. However, as seen in Figure 7, there was a significant interaction between activity and representation ($F_{(1,54)} = 10.43$, $p < .05$; $\eta^2_p = .16$). When using the text list, students generated more deep utterance when working with the user-generated representation compared to the system-provided list. For students using the spatial-semantic representation, the pattern was reversed (see Table 7). Students who worked with spatial semantic materials made significantly more deep utterances during problem solving when provided materials during study than students who were asked to generate their own materials. Students in the text list condition found the opposite pattern of results. Those who were asked to generate materials during study made significantly more deep utterances during problem solving when compared to students who provided materials (see Table 7.)

<u>Shallow utterances</u>

As shown in Figure 8, results demonstrated a significant main effect of representation type ($F_{(1,54)} = 9.40$, $p < .01$; $\eta^2_p = .15$) on the number of shallow utterances produced by students. Overall, students in the map condition made more shallow utterances than those in the list condition. There was not a significant main effect found for activity ($F < 1$). A significant interaction between activity and representation was identified ($F_{(1,54)} = 5.42$, $p < .05$; $\eta^2_p = .09$). Students in the map condition made fewer shallow utterances when working with system-provided materials compared to user-generated materials, whereas students in the list condition tended to make fewer shallow utterances when working with the user-generated materials compared to the system-provided materials (see Table 7).

Metacognitive utterances

As shown in Figure 9, there was a significant main effect of activity type ($F_{(1,54)} = 4.91$, $p < .05$; $\eta^2_p = .08$) on metacognitive utterances. Participants in system-provided conditions made more metacognitive utterances than those in the user-generated conditions during study (see Table 7.) There was no significant main effect of representation ($F < 1$). There was no significant interaction effect between activity and representation ($F < 1$).

## Effect of Learning Processes on Knowledge Outcomes

A bivariate correlation matrix (see Table 8) was generated to examine the potential relationships between coded learning processes and knowledge outcomes. There was a significant negative correlation between the proportion of shallow utterances and the proportion of recall questions answered correctly ($r(58) = -.30$, $p < .05$) There were no other significant correlations between learning processes and assessment scores (see Table 8). All assessment scores were significantly and positively correlated.

*Note: * $p < .05$; ** $p < .01$*

Table 2

*Means (standard deviations) for proportion correct on pre- and posttest assessments*

| | | Spatial-semantic Map | | Text List | |
|---|---|---|---|---|---|
| | | System-Provided ($n$ = 15) | User-Generated ($n$ = 16) | System-Provided ($n$ = 15) | User-Generated ($n$ = 14) |
| Pretest | | | | | |
| | Factual Knowledge | .63 (.09) | .55 (.12) | .60 (.11) | .57 (.13) |
| | Near Transfer | .48 (.16) | .44 (.10) | .48 (.12) | .45 (.17) |
| Posttest | | | | | |
| | Factual Knowledge | .69 (.12) | .59 (.21) | .67 (.08) | .63 (.12) |
| | Recall | .75 (.07) | .73 (.21) | .78 (.13) | .75 (.12) |
| | Near Transfer | .67 (.09) | .69 (.09) | .64 (.15) | .66 (.10) |

Table 3

*Total number of system moves by condition*

| Condition | Mean | St. Dev. |
|---|---|---|
| Text List ($n$ = 14) | 12.79 | 4.00 |
| Spatial-Semantic ($n$ = 16) | 12.63 | 4.60 |

Table 4

*Means and standard deviations for proportion of correct moves by representation type.*

| Condition | Mean | St. Dev. |
|---|---|---|
| Text List (*n* = 14) | .33 | .22 |
| Spatial-Semantic (*n* = 16) | .52 | .24 |

Table 5

*Means and standard deviations for proportion of representation completeness by representation type.*

| Condition | Mean | St. Dev. |
|---|---|---|
| Text List (*n* = 14) | .58 | .33 |
| Spatial-Semantic (*n* = 16) | .81 | .19 |

Table 6

*Number of total utterances (standard deviations)*

| | Spatial-semantic Map | Text List |
|---|---|---|
| System-Provided | 75.60 (21.29) | 78.36 (26.98) |
| User-Generated | 62.33 (22.04) | 61.07 (26.93) |

Table 7

*Mean proportion of utterances by code category (and standard deviations)*

| | Spatial-semantic Map | | Text List | |
|---|---|---|---|---|
| | System-Provided ($n$ = 15) | User-Generated ($n$ = 15) | System-Provided ($n$ = 14) | User-Generated ($n$ = 14) |
| Code Category | | | | |
| Deep category | .38 (.10) | .34 (.09) | .33 (.11) | .45 (.10) |
| Shallow category | .41 (.08) | .45 (.07) | .39 (.08) | .34 (.08) |
| Metacognitive category | .12 (.06) | .10 (.06) | .15 (.07) | .10 (.06) |

Table 8

*Correlations between knowledge measures and process-based results*

| Measure | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1. Proportion Shallow Utterances | – | | | | | |
| 2. Proportion Deep Utterances | -.46** | – | | | | |
| 3. Proportion Metacog. Utterances. | -.27* | -.63** | – | | | |
| 4. Proportion Factual Knowledge. | -.21 | .18 | .04 | – | | |
| 5. Proportion Recall | -.30* | -.07 | .20 | .36** | – | |
| 6. Proportion Near Transfer | -.17 | .079 | -.04 | .33* | .35** | – |

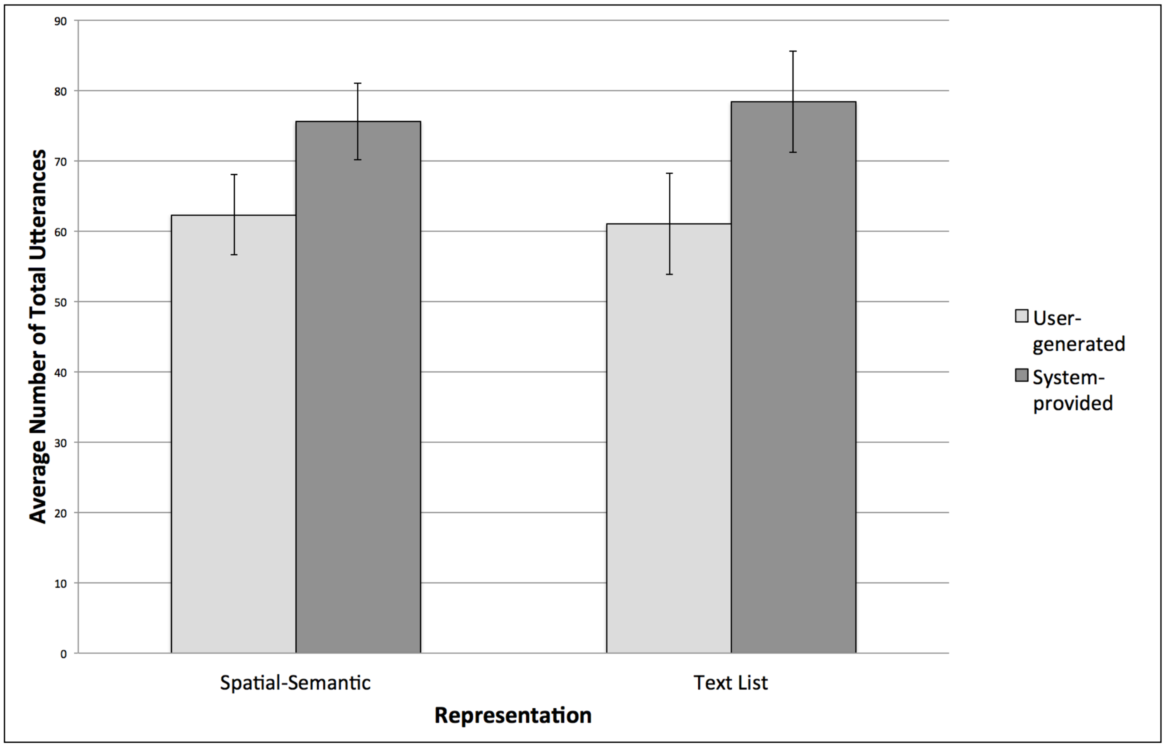


*Figure 6.* Total number of utterances made by condition.

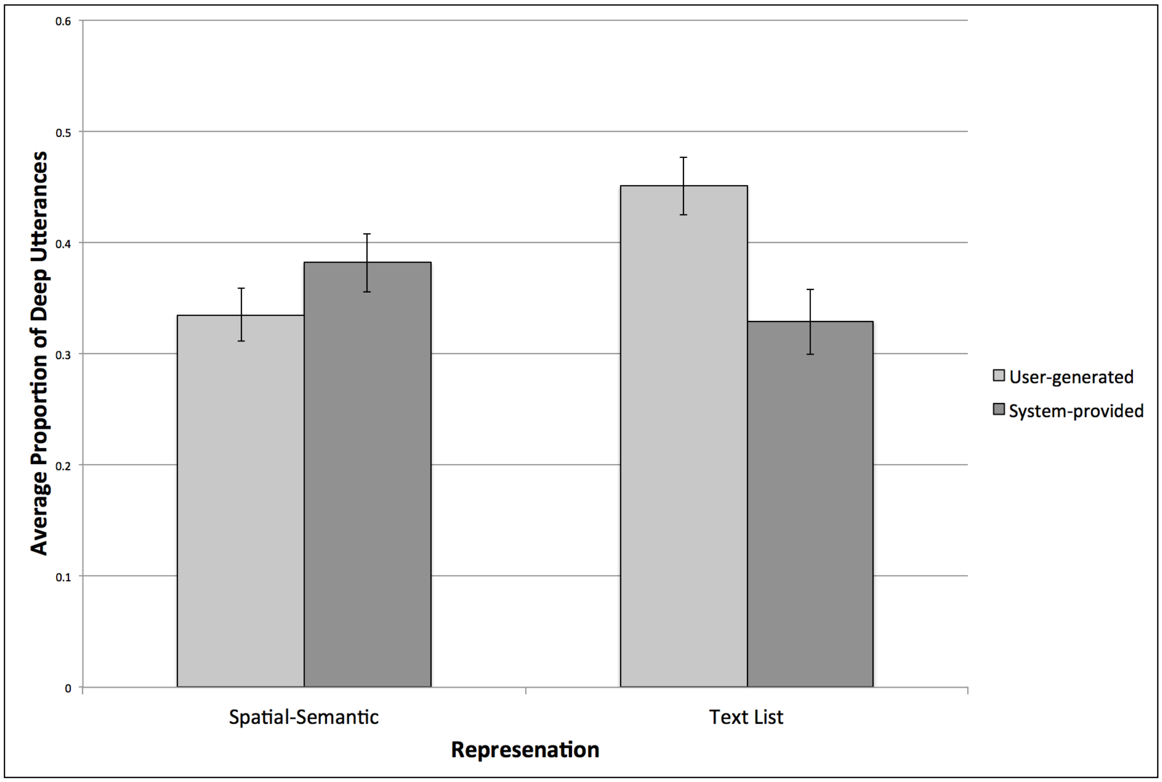


*Figure 7.* Average proportion of deep utterances by condition.

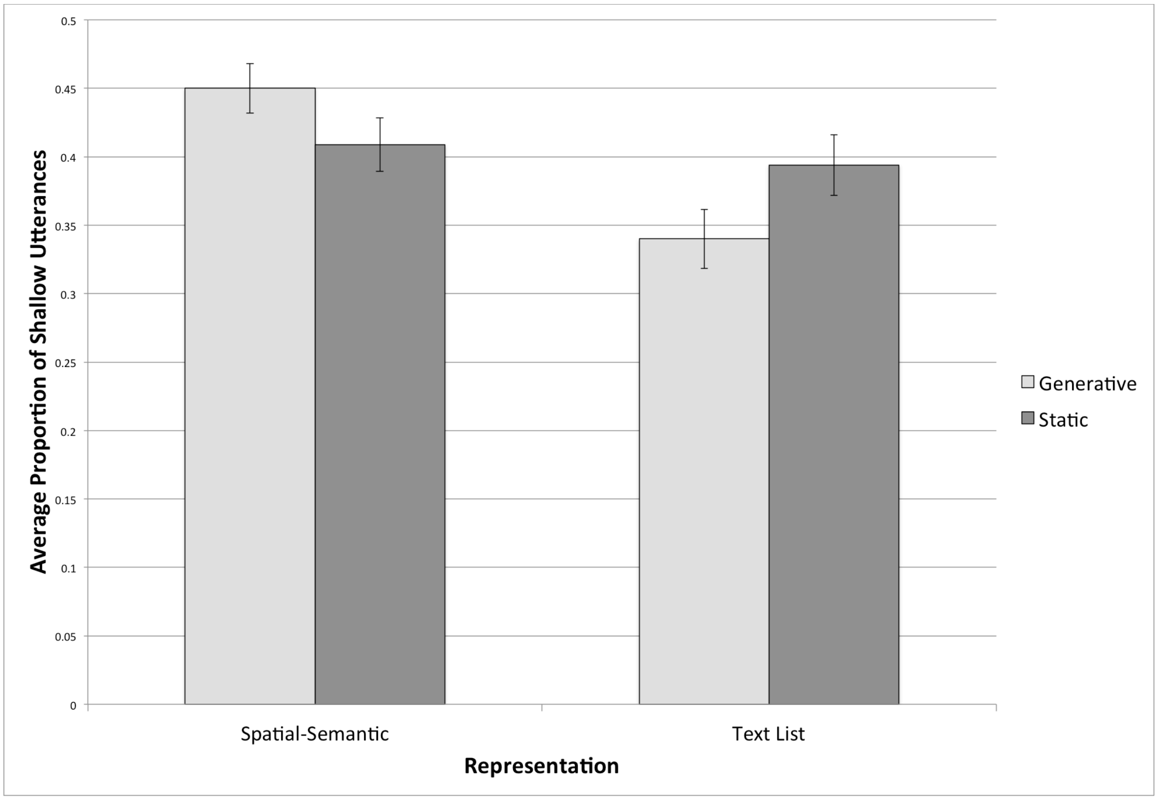


*Figure 8*. Average proportion of shallow utterances by condition.

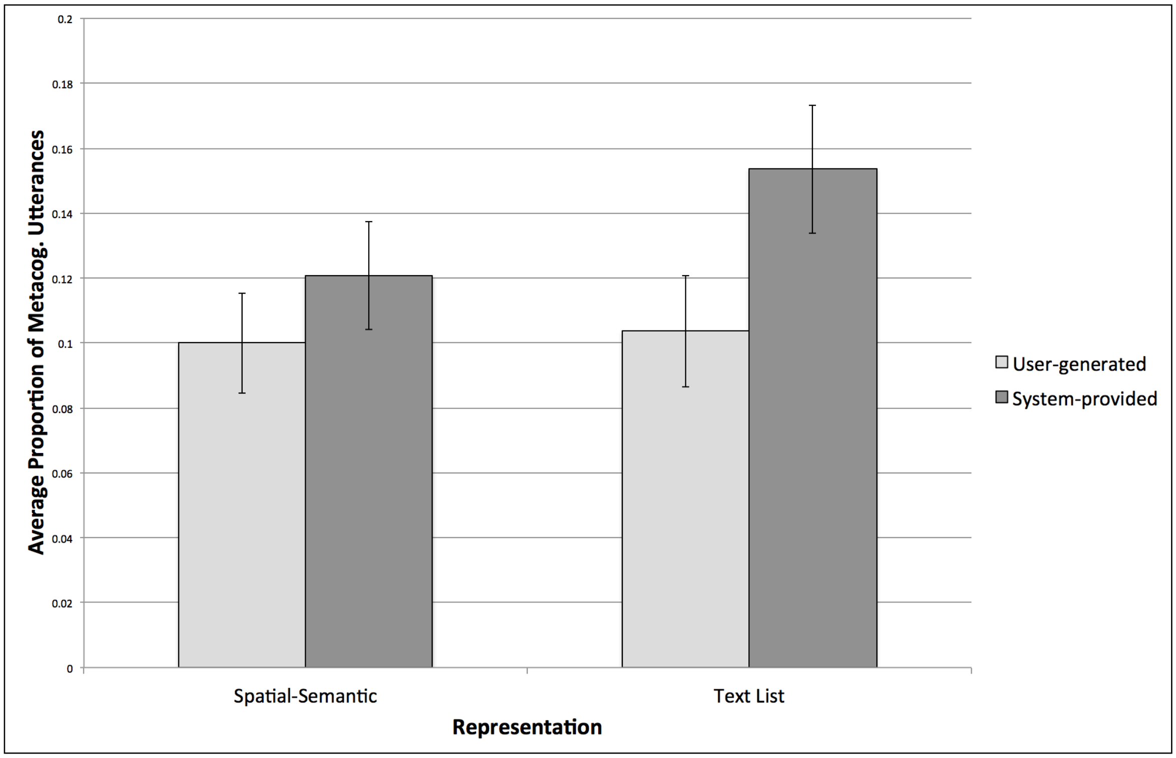


*Figure 9*. Average proportion of metacognitive utterances by condition.

# CHAPTER 4

# DISCUSSION

## Do Domain Overviews Facilitate Deeper Understanding in Complex Reasoning Tasks?

The first research question examined whether having a domain overview, in this case a spatial-semantic map representation, facilitated deeper understanding of a complex reasoning task. Overall, results suggested that learners who worked with a spatial-semantic representation did not improve their conceptual understanding significantly more than learners who used text list materials. Results showed no significant benefits of using a spatial-semantic map on factual knowledge, recall, or near transfer measures. These results are not consistent with prior research on concept maps, which generally has shown that a spatial-semantic representation of a complex topic increases comprehension outcomes.

One possible explanation for the spatial-semantic map's lack of impact is that the domain content used in the current research did not require learners to engage in the types of conceptual/relational processing that spatial-semantic maps might be expected to support. Most spatial-semantic map research finds benefit in providing learners with a cognitive structure to the complex information (Lambiotte & Dansereau, 1992), by making central ideas more salient and facilitating an understanding of the macrostructure

(Chmielewski & Danserau, 1998; Hall & O'Donnell, 1996), and by helping learners recall more central ideas of the topic (Adesope & Nesbit, 2013). In this study, the spatial-semantic map was more akin to a decision map. A decision map is visually similar to a concept map, but is essentially a hierarchical flow chart that indicates decisions and considerations at certain junctures of the problem-solving process. It does not communicate conceptual relationships between nodes, nor does it require the student to integrate and synthesize between node content. It simply provides the learner with a method to analyze a specific type of problem. Future concept map research in the law domain should choose a topic with complex concepts that can be represented by a traditional concept map, such as constitutional law.

Another explanation could be that the instruments used to measure differences in knowledge were not sufficiently sensitive. The statute of frauds is a relatively narrow and specific subject of contract law. The subject matter expert provided near transfer problems that were quite similar and therefore required similar thought processes and approaches to solve. This may not have provided students with enough opportunities to apply their knowledge in meaningful and nuanced ways. The correlation matrix shown in Table 8 is consistent with this possibility. Students who engaged in deep cognitive processes during study should be more likely to successfully answer near transfer questions as they (are intended to) require the students to go beyond the content, make inferences, and connect incoming information with their prior knowledge. Likewise, those who engaged in more shallow processes during study should perform well on factual knowledge and recall measures, but would be expected to perform poorly on near transfer questions that required deeper understanding to answer correctly. However, the only significant correlation found was that shallow utterances had a significant negative correlation with performance on recall measures – which typically would be considered a measure of more shallow knowledge. The proportion of deep utterances made by a participant was not correlated with any of the knowledge measures used in the current study. In addition, the assessments also showed significant, positive correlations with each other, suggesting that they did not measure distinct forms of knowledge. Future research in the statute of frauds should work to develop more sensitive and distinct measures of recall and understanding. For example, more complex hypotheticals in the statute of frauds topic should be used – similar to problems one might encounter in legal practice – to determine whether or not the participant can apply their knowledge in a variety of situations that would require inference and other deep processes.

Finally, participants had limited exposure to the study materials. Participants in this study examined their assigned materials for 5 minutes of study time, then had up to 5 minutes to solve the hypothetical problems. This means that a participant had, at most, 15 minutes of exposure to the study materials. This may not have been enough time for a participant to encode the representation and process it deeply, therefore promoting only a superficial understanding of the materials.

## Does the Generation Effect Enhance the Utility of the Representation?

The second research question examined whether or not having to generate a representation (spatial-semantic map or text list) would enhance its utility. Overall, results showed that participants who generated any representation during study performed no better at posttest measures (factual knowledge, recall, and near transfer) than those that did not. These results are inconsistent with previous research, which has shown that asking students to create some portion of their learning materials results in deeper conceptual understanding of a topic (Chang et al., 2002; Chi, 1989; Hauser et al., 2006). There could be a number of explanations for the lack of impact resulting from participant generation in the current research.

As previously mentioned, learners had a limited time with the study materials. Students in the user-generated conditions not only had to study the representation, but also had to generate their representation through the interactive drag-and-drop features of the interface. Many students who generated their representation, in both spatial-semantic and text list conditions, failed to complete the entire representation in the time allowed during study (*M* representation completeness after study: 81% spatial-semantic condition; 58% text list condition). Thus, for students in the user-generated conditions, the majority of time during study was spent constructing the representation as opposed to processing the content.

It also is possible that the current research failed to capture longer-term benefits of generation. Prior research has demonstrated that the benefits of user-generation do not always manifest at an immediate posttest; sometimes generation fails to show benefits at immediate posttest that are apparent – and significant – at delayed posttest (Butcher & Aleven, 2013). Due to the use of multiple research sites in the current research, a delayed posttest was not possible. Future research should explore the use of a delayed posttest to examine longer-term impact of student generation during learning.

Another explanation is that the generation effect has been shown to improve explicit memory performance, such as recall and recognition, but not to improve implicit memory performance (Jacoby, 1983; Roediger, 1990). Law students may have well-developed implicit knowledge and strategies for solving legal hypotheticals that were used as opposed to explicitly recalling and implementing the steps suggested in generating the semantic-spatial map or text list. If the posttest measures had tested a participant's ability to *recall* the steps (i.e., an explicit memory task) in solving a statute of frauds problem, then Jacoby's 1983 research suggests that we may have seen a benefit in generation of a semantic-spatial map or text list. However, since the measures asked students to not recall the steps, but rather *transfer* the steps to a problem solving task (i.e., an implicit memory task), the task could have been engaging implicit memory and therefore the generation effects might not be as pronounced.

## What Is the Effect of Domain Overviews and Generation on Self-explanations?

Examining students' utterances during learning provides insight into the depth of their cognitive processes during learning. The current research found a significant interaction between representation type and activity type when looking at deep utterances produced by participants during problem solving. Participants who studied while generating a text list representation produced significantly more deep utterances during problem solving than those who studied a system-provided text list representation. The opposite was true for participants who studied with a spatial-semantic representation. Participants who studied while generating a spatial-semantic representation produced significantly fewer deep utterances than those studying with a system-provided map.

Why might this be the case?

Map-based materials are inherently complex. Not only do they depict the relevant concepts and ideas of a topic, they also show the structure of relationships between nodes in the representation. Asking participants to generate a map representation and study that representation in the time allowed may be inherently too demanding for learners. When the spatial-semantic map was provided to the participants, they may have been better able to focus on the concepts depicted and the flow between decisions in the map, allowing students to process the representation more deeply.

The text list was a more simplistic representation than the map, taking the form of a numbered list. When this representation was provided to participants during study, participants generated more shallow utterances during problem solving. The numbered list – due to its linear structure and similarity to outlines or note taking format – may not have encouraged students to process the decision-making structure very deeply. On the other hand, participants who were asked to create the numbered list likely had to determine where and how to place nonlinear content in a linear format. Thus, they may have had to process connections more deeply in order to place nodes into a representation that did not easily match the overall flow of the decision process. This is similar to previous research showing that (higher knowledge) learners can learn more deeply when an outline is mismatched to textual materials (Mannes & Kintsch, 1987). When learners are working in a familiar domain, it may be helpful to encourage deeper processing by making representation tasks more demanding. However, results from the map conditions suggest that complex representations may have enough (inherent) demand that additional demand (implemented in a generation task) may be unhelpful.

The idea that system-provided materials allowed participants to engage with the materials more freely than those in the generative conditions is supported by the results. Those in the system-provided conditions made a greater number of utterances compared to those in the user-generated conditions. This suggests that, because those in the system-provided condition had a complete representation, they were given an opportunity to fully consider the information provided in the representation, free of the extra cognitive effort that might occur when a user is asked to generate materials.

Future research should explore the effect of partially completed representations on user-generated conditions. A partially completed representation may reduce the overall complexity of the user-generated representation and allow the participant to engage in more meaningful interactions with the representation as they study.

## Conclusions

This study explored the effectiveness of concept maps and generation as tools for deep comprehension in legal education in a computer-based learning environment. Although overall findings were limited, the current study suggests that there may be important trade-offs between the representation types and the amount of generation that is optimal for learning. Future research should be conducted using other subjects in legal education to gain additional insight into the efficacy of concept maps and user-generation as a technique to encourage deeper learning. A careful consideration of topical materials and learning environments will be necessary to determine whether or not concept maps and generation effects will have the desired effects.

APPENDIX

| Code category | Subcode Name | Description | Example |
|---|---|---|---|
| Deep | Elaboration: Application of PK | Utterances that are inferences stemming from information previously gained prior to the study. This also includes information learned from the multimedia materials. | "That sounds like an exception possibly under the UCC." |
| | Elaboration: From hypothetical | Utterances that are an explanation of what the hypothetical means that goes beyond paraphrasing. Making sense out of the situation in the hypo. These will also be things that are constructed from the information and not explicitly mentioned. | "There it specifically says it's an oral agreement, meaning that there's no writing that satisfies the statute." |
| | Elaboration: From list item | Utterances that are an explanation or elaboration as a result of a node for participants in the text list condition | "They made an oral contract which [was] explicitly stated in the facts." |
| | Elaboration: from node item | Utterances that are an explanation or elaboration as a result of a node for participants in the spatial semantic condition. | "[B]ut from the framework, I'm going to stick with because this contract is not in writing, uh, and it, the contract, uh, would need to be in writing due to the statute." |
| | Legal Reasoning: | Utterances that are | "It appears that Ben |

| | | | |
|---|---|---|---|
| | Application of Rule or Law | statements of the rules that are pertinent in deciding the issue at hand. This will often look like legal problem solving or decision-making. | and Jerry and Moo Juice are both merchants so the merchant exception would apply." |
| | Legal Reasoning: Assumption from the Hypothesis | Utterances where the learner is making an assumption about the hypothetical. They're inferring from the facts of the case to make it fit. | "I'm going to assume that Bob is a merchant because he is buying so much ale." |
| | Legal Reasoning: Change the Hypothesis | Utterances in which the participant changed or tweaked elements of the hypothetical to gain additional understanding and insight. | "If, I guess to change the facts to, um, say that it wouldn't be enforceable, it wouldn't be enforceable if this was just normal milk." |
| | Prior Knowledge: Class reference | Utterances in which a participant makes a reference to a class they had taken. | "[A]nd combining the two writings which I think they did in some case that we had." |
| | Prior Knowledge: Implicit video reference | Utterances in which a participant makes reference to information gained within the instructional videos without explicitly stating it was from the video. | "[B]ut it was whether or not, uh, it was a special order." |
| | Prior Knowledge: Video reference | Utterances in which a participant directly refers to prior knowledge gained from within the instructional videos. | "And I remember in the video there were five elements, uh, that I would walk through to see whether or not, uh, this fell into the special product exception under the UCC and, um." |
| Shallow | Answer: Answer a prompt | Utterances in which the participant declaratively | "In this case it was." |

| | | | |
|---|---|---|---|
| | | answers a prompt from their representation. Typically summarized in one sentence or less. | |
| | Answer: Call of the question | Utterances in which the participant declaratively answers the call of the question. Typically summarized in one sentence. | “In this case it sounds like Moo Juice would be able to bring in evidence of the oral contract under the UCC” |
| | Materials: Negative opinion | Utterances in which a participant negatively comments on the quality of the substance experimental materials | “Those are useless facts to me.” |
| | Materials: Response/reaction negative | Utterances in which the participant negatively comments on the overall structure of the experimental materials. | “Okay. So. This one has a lot more detail than the last one.” |
| | Materials: Response/reaction positive | Utterances in which the participant positively comments on the overall structure of the experimental materials. | “I like this.” |
| | Materials: Suggested modification | Utterances in which the participant suggests a modification to the experimental materials. | “[U]h, there’s a typo.” |
| | Paraphrase: List item | Utterances in which the participant paraphrases an sentence from the text list materials. | “Are there any exceptions that apply?” |
| | Paraphrase: Map item | Utterances in which the participant paraphrases a node from the spatial-semantic materials. | “So the first question looking at the tree again is, ‘is the contract between the parties within the statute.’” |
| | Paraphrase: Problem text | Utterances in which the participant paraphrases the hypothetical text. | “And Moo Juice sues Ben and Jerry’s for breach of contract.” |
| | Reading: Hypothetical/Problem | Utterances in which the participant reads the hypothetical text | “Um, Chocolate milk that is made of very finely ground |

| | | | |
|---|---|---|---|
| | | verbatim. | Mayan cocoa beans and contains added milk fat and vitamin D.” |
| | Reading: List Node | Utterances in which the participant paraphrases a sentence from the text list. | “Is the contract between the parties within the statute?” |
| | Reading: Map Node | Utterances in which the participant paraphrases a node from the spatial-semantic map. | “So, ‘is the contract between the parties within the statute under the UCC?’” |
| Metacognitive | Metacognitive: Negative | Utterances in which the participant expressed doubt or uncertainty of their thoughts or knowledge. | “I didn’t know if it was an oral agreement or a written agreement.” |
| | Metacognitive: Positive | Utterances in which the participant has a neutral or positive expression of their thoughts or knowledge. | “Well, if I look back here I remember thinking that there was no writing.” |
| | Metacognitive: Strategic planning | Utterances in which the participant structures a plan for approaching the hypothetical problem. | “First I’m going to read the hypo.” |
| | Writing: Arithmetic | Utterances where the participant talks out the math they are doing. | “So, 50 times 10 equals $500” |
| | Writing: Drawing | Utterances where the participant talks out a diagram they are creating. | “So an arrow from MJ to BJ, and number 500.” |
| | Writing: General | Utterances where the participant talks about what they are writing down, in general. | “So Bob and Sally. I’m just gonna leave off last names.” |
| | Writing: Note | Utterances where the participant makes a “mental” note by writing it down on paper. | “I’m going to make a note of that” |

## REFERENCES


Adesope, O. O., & Nesbit, J. C. (2013). Animated and static concept maps enhance learning from spoken narration. *Learning and Instruction*, *27*, 1-10.

Ainsworth, S., & Loizou, A. (2003). The effects of self-explaining when learning with text or diagrams. *Cognitive Science*, *27*(4), 669-681.

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. *Journal of the Learning Sciences*, *4*(2), 167-207.

Bodemer, D., Ploetzner, R., Bruchmüller, K., & Hacker, S. (2005). Supporting learning with interactive multimedia through active integration of representations. *Instructional Science*, *33*, 73-75.

Bodemer, D., Ploetzner, R., Feuerlein, I., & Spada, H. (2004). The active integration of information during learning with dynamic and interactive visualizations. *Learning and Instruction*, *14*(3), 325-341.

Bransford, J. D., & Schwartz, D. L. (1999). Rethinking transfer: A simple proposal with multiple implications. *Review of Research in Education*, *24*, 61-100.

Butcher, K. R., & Kintsch, W. (2003). Text comprehension and discourse processing. In A.F. Healy & R.W. Proctor (Eds.), *Handbook of psychology, volume four: experimental psychology* (2nd ed., pp. 575–595). Hoboken, NJ: Wiley.

Chang, K. E., Sung, Y. T., & Chen, I. D. (2002). The effect of concept mapping to enhance text comprehension and summarization. *The Journal of Experimental Education*, *71*(1), 5-23.

Chi, M. T. H. (1997). Quantifying qualitative analyses of verbal data: A practical guide. *Journal of the Learning Sciences*, *6*(3), 271-315.

Chi, M. T. H. (2000). Self-explaining expository texts: The dual processes of generating inferences and repairing mental models. In R. Glaser (Ed.), *Advances in instructional psychology* (pp. 161–238). Mahwah, NJ: Lawrence Erlbaum Associates.

Chi, M. T. H. (2009). Active-constructive-interactive: A conceptual framework for differentiating learning activities. *Topics in Cognitive Science*, *1*, 73-105.

Chi, M. T. H., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science*, *13*, 145-182.

Chi, M. T. H., de Leeuw, N., Chiu, M., & Lavancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive Science*, *18*, 439–477.

Chi, M. T. H., & Glaser, R. (1985). Problem-soving ability. In R. J. Sternberg (Ed.), *Human abilities: An information-processing approach* (pp. 227-250). New York, NY: W. H. Freeman & Co.

Chi, M. T. H., Glaser, R., & Rees, E. (1982). Expertise in problem solving. In R. J. Sternberg (Ed.), *Advances in the psychology of human intelligence* (Vol. 1, pp. 7-75). Hillsdale, NJ: Erlbaum.

Chi, M. T., Feltovich, P. J., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science*, *5*(2), 121-152.

Chmielewski, T. L., & Dansereau, D. F. (1998). Enhancing the recall of text: Knowledge mapping training promotes implicit transfer. *Journal of Educational Psychology*. *90*(3), 407-413.

Chularut, P., & DeBacker, T. K. (2004). The influence of concept mapping on achievement, self-regulation, and self-efficacy in students of English as a second language. *Contemporary Educational Psychology*, *29*(3), 248-263.

De Leeuw, N., & Chi, M. T. H. (2003). Self-explanation: Enriching a situation model or repairing a domain model? In G. Sinatra & P. Pintrich (Eds.), *Intentional conceptual change* (pp. 55-78). Hillsdale, NY: Lawrence Erlbaum Associates.

Fruehwald, S. (2012). *How to become an expert law teacher by understanding the neurobiology of learning*. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2115768

Gurlitt, J., & Renkl, A. (2010). Prior knowledge activation: How different concept mapping tasks lead to substantial differences in cognitive processes, learning outcomes, and perceived self-efficacy. *Instructional Science*, *38*, 417-433.

Guyot, S. (2010). Learning as top priority in the law school classroom. *The Law Teacher, 17*(1), 12-13.

Hauser, S., Nückles, M., & Renkl, A. (2006). Supporting concept mapping for learning from text. In *Proceedings of the 7th international Conference on Learning Sciences* (Bloomington, Indiana, June 27 - July 01, 2006). International Conference on Learning Sciences, 243-249.

Hirshman, E., & Bjork, R. A. (1988). The generation effect: Support for a two-factor theory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 484-494.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist*, *38*(1), 23-31.

Kintsch, W. (1988). The role of knowledge in discourse comprehension: A construction-integration model. *Psychological Review*, *95*(2), 163-182.

Kintsch, W. (1994). Text comprehension, memory, and learning. *American Psychologist*, *49*(4), 294-303.

Kintsch, W. (2005). An overview of top-down and bottom-up effects in comprehension: The CI perspective. *Discourse Processes, 39*(2-3), 125-128.

Koedinger, K. R., & Aleven, V. (2007). Exploring the assistance dilemma in experiments with cognitive tutors. *Educational Psychology Review*, *19*(3), 239-264.

Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (1997). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education*, *8*, 30-43.

Jacoby, L. L. (1978). On interpreting the effects of repetition: Solving a problem versus remembering a solution. *Journal of Verbal Learning and Verbal Behavior*. *17*(6), 649-667.

Jacoby, L. L. (1983). Remembering the data: Analyzing interactive processes in reading. *Journal of Verbal Learning and Verbal Behavior*, *22*(5), 485-508.

Lambiotte, J. G., & Dansereau, D. F. (1992). Effects of knowledge maps and prior knowledge on recall of science lecture content. *Journal of Experimental Education*, *60*(3), 189-201.

Lustbader, P. (1996). From dreams to reality: The emerging role of law school academic support programs. *University of San Francisco Law Review, 31*, 839-860.

Mannes, S. M., & Kintsch, W. (1987). Knowledge organization and text organization. *Cognition and Instruction*, *4*(2), 91-115.

McElroy, L. A., & Slamecka, N. J. (1982). Memorial consequences of generating nonwords: Implications for semantic-memory interpretations of the generation effect. *Journal of Verbal Learning and Verbal Behavior*, *21*(3), 249-259.

Novak, J., & Gowin, D. B.. (1984). *Learning how to learn*. New York, NY: Cambridge University Press.

O'Donnell, A. M., Dansereau, D. F., & Hall, R. H. (2002). Knowledge maps as scaffolds for cognitive processing. *Educational Psychology Review*, *14*(1), 71-86.

Perkins, D.N., & Salomon, G. (1992). *Transfer of learning: Contribution to the International Encyclopedia of Education* (2nd ed.). Oxford, England: Pergamon Press. Retrieved from http://learnweb.harvard.edu/alps/thinking/docs/traencyn.pdf

Renkl, A. (1997). Learning from worked-out examples: A study on individual differences. *Cognitive Science*, *21*(1), 1-29.

Renkl, A., Stark, R., Gruber, H., & Mandl, H. (1998). Learning from worked-out examples: The effects of example variability and elicited self-explanations. *Contemporary Educational Psychology*, *23*(1), 90-108.

Roediger, H. L. (1990). Implicit memory: Retention without remembering. *American Psychologist*, *45*(9), 1043.

Roy, M., & Chi, M. T. H. (2005). The self-explanation principle in multimedia learning. In R. E. Mayer (Ed.), *Cambridge handbook of multimedia learning* (pp. 271–286). New York, NY: Cambridge University Press.

Schwartz, D. L., & Bransford, J. D. (1998). A time for telling. *Cognition and Instruction*, *16*, 475–522.

Schwartz, M. H. (2001). Teaching law by design: How learning theory and instructional design can inform and reform law school. *San Diego Law Review*, *38*, 347-462.

Slamecka, N., & Graf, P. (1978). The generation effect: Delineation of a phenomenon. *Journal of Experimental Psychology: Human Learning and Memory*, *4*(6), 592-604.

Wharton, C., & Kintsch, W. (1991). An overview of construction-integration model: A theory of comprehension as a foundation for a new cognitive architecture. *ACM SIGART Bulletin*, *2*(4), 169-173.

Whitehead, A. (1929). *The aims of education and other essays*. New York, NY: The Macmillan Company.

Wittrock, M. C. (1989). Generative processes of comprehension. *Educational Psychologist*, *24*(4), 345-376.