Improving Metacomprehension And Learning Through Graduated Concept Mod

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IMPROVING METACOMPREHENSION AND LEARNING THROUGH GRADUATED CONCEPT MODEL DEVELOPMENT

by

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ABSTRACT

Mental model development, deeper levels of information processing, and elaboration are critical to learning. More so, individuals’ metacomprehension accuracy is integral to making improvements to their knowledge base. In other words, without an accurate perception of their knowledge on a topic, learners may not know that knowledge gaps or misperceptions exist and, thus, would be less likely to correct them. Therefore, this study offered a dual-process approach that aimed at enhancing metacomprehension. One path aimed at advancing knowledge structure development and, thus, mental model development. The other focused on promoting a deeper level of information processing through processes like elaboration. It was predicted that this iterative approach would culminate in improved metacomprehension and increased learning.

Accordingly, using the Graduated Concept Model Development (GCMD) approach, the role of learner-generated concept model development in facilitating metacomprehension and knowledge acquisition was examined. Concept maps have had many roles in the learning process as mental model assessment tools and advanced organizers. However, this study examined the process of concept model building as an effective training tool. Whereas, concept maps functioning as advanced organizers are certainly beneficial, it would seem that the benefits of having a learner examine and amend the current state of their knowledge through concept model development would prove more effective for learning. In other words, learners looking at an advanced organizer of the training material may feel assured that they have a thorough
understanding of it. Only when they are forced to create a representation of the material would the gaps and misperceptions in their knowledge base likely be revealed. In short, advanced organizers seem to rely on recognition, where concept model development likely requires recalling and understanding ‘how’ and ‘why’ the interrelationships between concepts exist. Therefore, the Graduated Concept Model Development (GCMD) technique offered in this study was based on the theory that knowledge acquisition improves when learners integrate new information into existing knowledge, assign elaborated meanings to concepts, correct misperceptions, close knowledge gaps, and strengthen accurate connections between concepts by posing targeted questions against their existing knowledge structures. This study placed an emphasis on meaningful learning and suggested a process by which newly introduced concepts would be manipulated for the purpose of improving metacomprehension by strengthening accurate knowledge structures and mental model development, and through deeper and elaborated information processing. Indeed, central to improving knowledge deficiencies and misunderstandings is metacomprehension, and the constructing of concepts maps was hypothesized to improve metacomprehension accuracy and, thus, learning.

This study was a one-factor between-groups design with concept map type as the independent variable, manipulated at four levels: no concept map, concept map as advanced organizer, learner-built concept map with feedback, and learner-built concept map without feedback. The dependent variables included performance (percent correct) on a declarative and integrative knowledge assessment, mental model development, and metacomprehension accuracy. Participants were 68 (34 female, 34 male, ages 18-35, mean age = 21.43) undergraduate students from a major southeastern university.
Participants were randomly assigned to one of the four experimental conditions, and analysis revealed no significant differences between the groups. Upon arrival, participants were randomly assigned to one of the four experimental conditions. Participants then progressed through the three stages of the experiment. In Stage I, participants completed forms regarding informed consent, general biographical information, and task self-efficacy. In Stage II, participants completed the self-paced tutorial based on the Distributed Dynamic Decision Making (DDD) model, a simulated military command and control environment aimed at creating events to encourage team coordination and performance (for a detailed description, see Kleinman & Serfaty, 1989). The manner by which participants worked through the tutorial was determined by their assigned concept map condition. Upon finishing each module of the tutorial, participants then completed a metacomprehension prediction question. In Stage III, participants completed the computer-based knowledge assessment test, covering both declarative and integrative knowledge, followed by the metacomprehension postdiction question. Participants then completed the card sort task, as the assessment of mental model development. Finally, participants completed a general study survey and were debriefed as to the purpose of the study. The entire experiment lasted approximately 2 to 3 hours.

Results indicated that the GCMD condition showed a stronger indication of metacomprehension accuracy, via prediction measures, compared with the other three conditions (control, advanced organizer, and feedback), and, specifically, significantly higher correlations than the other three conditions in declarative knowledge. Self-efficacy measures also indicated that the higher metacomprehension accuracy correlation observed in the GCMD condition was likely the result of the intervention, and not due to
differences in self-efficacy in that group of participants. Likewise, the feedback and GCMD conditions led to significantly high correlations for metacomprehension accuracy based on levels of understanding on the declarative knowledge tutorial module (Module 1). The feedback condition also showed similar responses for the integrative knowledge module (Module 2). The advanced organizer, feedback, and GCMD conditions were also found to have significantly high correlation of self-reported postdiction of performance on the knowledge assessment and the actual results of the knowledge assessment results. However, results also indicated that there were no significant findings between the four conditions in mental model assessment and knowledge assessment. Nevertheless, results support the relevance of accurate mental model development in knowledge assessment outcomes.

Retrospectively, two opposing factors may have complicated efforts to detect additional differences between groups. From one side, the experimental measures may not have been rigorous enough to filter out the effect from the intervention itself. Conversely, software usability issues and the resulting limitations in experimental design may have worked negatively against the two concept mapping conditions and, inadvertently, suppressed effects of the intervention. Future research in the GCMD approach will likely review cognitive workload, concept mapping software design, and the sensitivity of the measures involved.
To my family. Thank you for all your love and support. Mostly thank you for a lifetime of examples in integrity, strength, and commitment.
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LIST OF ABBREVIATIONS

Adv Org  Advanced Organizer
APA     American Psychological Association
AVI     Audio-Video-Interleaved
DDD     Distributed Dynamic Decision Making
GCMD    Graduated Concept Model Development
GPA     Grade Point Average
FITS    Fill-in-the-Structure
LTM     Long Term Memory
MetaKnowledge M1  Level of Understanding Module 1
MetaKnowledge M2  Level of Understanding Module 2
MetaPost Metacomprehension Postdiction
MetaPre M1  Metacomprehension Prediction Module 1
MetaPre M2  Metacomprehension Prediction Module 2
MMA      Mental Model Accuracy
SAT      Scholastic Aptitude Test
SE       Self-Efficacy
SME      Subject Matter Expert
TPL-KATS Team Performance Laboratory – Knowledge
Assessment Tool Suite
INTRODUCTION

Although cognitive ability is the primary predictor of performance (Georgiadis & Efklides, 2000), learning success is also greatly contingent on the learner’s ability to self-evaluate via processes such as self-regulated learning and metacognition (Zimmerman, 1998). In other words, given equivalent level of intelligence, individuals with a greater ability in self-regulation and metacognition are more likely to correctly integrate knowledge than those with weak self-regulating and metacognition skills; novices’ learning performance can be predicted by the sum of their intellectual ability and metacognitive skill (see Elshout & Veenman, 1992). As domain-specific knowledge and skills develop, the metacognitive skills become more domain-specific (Glaser & Chi, 1988) and less reliant on intellectual ability (Veenman, Elshout, & Hoeks, 1993). Indeed, it is the cognitive process of metacomprehension, a component of metacognition, which focuses on learners’ understanding of their knowledge in an area (Brown, 1975). Successful learners are active learners, who think about, interact with, and even control their learning environment and experience (Zimmerman, 1998). As such, it is important to understand these cognitive processes that allow learners to have a substantial role in their learning.

In discussing self-regulated learning, metacognition, and metacomprehension, it is essential to delineate the relationship between these processes. In general, metacognition is a component of self-regulated learning and metacomprehension is a facet of metacognition. Self-regulated learning is characterized as the active regulating of one’s
cognition (metacognition), motivation, and behavior through various processes in an
effort to achieve a goal (Zimmerman, 1989). Metacognition is defined as individuals’
knowledge of, and ability to regulate, their cognitive processes (Flavell, 1979; Osman &
Hannafin, 1992; Schraw, 1998). Metacognitive knowledge encompasses knowledge of
the person’s characteristics, the task information provided and demand required, and the
effectiveness of various strategies. These factors are evaluated so that effective processes
are selected in attaining a given outcome (Flavell, 1979). One’s metacognitive skills are
at the basis of how effectively cognitive resources are allocated (Halpern, 1998;
Veenman & Elshout, 1999). Metacognition is further identified as one of four factors
impacting knowledge acquisition: domain knowledge, inference-making ability, working
memory, and metacognition (Britton, Stimson, Stennett, & Gulgoz, 1998). For purposes
of this study, metacomprehension, a primary facet of metacognition, is defined as
learners’ understanding of their knowledge base (Brown, 1975) and knowledge of and
ability to regulate their comprehension, including identifying and compensating for
failures in comprehension (Osman & Hannafin, 1992). A thorough understanding or
acquisition of a skill is distinguished by how well one is able to explain the principles
behind it, recognize probable variations, and adapt the skill to varying demands (Hatano
& Inagaki, 1983). Thus, equally important as content knowledge is the ability for the
learner to recognize the criteria of when to employ certain strategies (Osman & Hannafin,
1992). As such, metacomprehension is the regulatory process central to this study.
Metacomprehension and Learning

Research findings support that an increase in metacognitive and metacomprehension abilities positively influence learning. For example, the introspective processes of metacognition and metacomprehension have a significant impact on various aspects of learning, such as self-regulated learning (e.g., Hofer, Yu, & Pintrich, 1998; Winne & Stockley, 1998), oral and written communication and comprehension (Flavell, 1979), problem solving (e.g., Davidson, Deuser & Sternberg, 1994; Mayer, 1998), memory (e.g., Bjork, 1994; Brown, 1978), and development of expertise (e.g., Smith, Ford & Kozlowski, 1997; Sternberg, 1998). In addition, Britton, Stimson, Stennett, and Gulgoz, (1998) found that metacognitive ability is directly related to how well connections between key points in text are made. Likewise, metacognitive abilities, like metacomprehension, impact knowledge acquisition, skilled performance, and self-efficacy; which, in turn, are directly useful in transferring knowledge to complex tasks (Ford, Smith, Weissbein, Gully, & Salas, 1998). Ford et al. (1998) also emphasized that self-directed learning is essential to developing and effectively using metacognitive processes.

Determining how training constructs can be manipulated to assist learners in the cognitive practices of metacognition and metacomprehension has been the primary focus of several researchers. For instance, studies have shown the influence of instructional techniques on metacognitive related attributes, such as metacomprehension (e.g., Gourgey, 1998; Hartman, 2001a, 2001b; Maqsud, 1998; McInerney, McInerney &
Marsh, 1997; Schmidt & Ford, 2001; Volet, 1991). Meloth (1990) focused on improving knowledge of cognition with 3rd grade students and increased their reading comprehension and use of strategies. Similarly, Manning (1992) taught monitoring strategies to a 4th grade class to use with guided reading lessons, leading to improved reading comprehension, reading strategy knowledge, and attitudes toward reading. Finally, low-skill 4th grade students were taught to ask ‘who, what, when, where, and why’ as a means of monitoring their reading comprehension (Short & Ryan, 1984). The comprehension level of the low-skill readers rose to the level of the skilled students, further demonstrating the effectiveness of training methods focused on enhancing metacomprehension.

A small number of studies have shown a direct positive relationship between metacomprehension and knowledge acquisition, or learning. In examining training of complex tasks, Fiore, Cuevas, Scielzo, and Salas (2002) found that metacomprehension accuracy had a positive relationship with knowledge acquisition assessments. In addition, a study by Cuevas, Fiore, and Oser (2002) study focused on addressing how to assist learners improve their metacomprehension skills through training manipulations. In that study, the authors examined the use of diagrams as a means of relating key points of the training text and facilitating the development of knowledge structures and mental models. Results indicated the presence of diagrams improved metacomprehension (as defined by Brown as cited in Osman & Hannafin, 1992), especially for learners of lower verbal ability. These findings also revealed improvements in integrative knowledge, accuracy of mental models, and instructional efficiency, as well as demonstrating, how metacomprehension ability translates to task performance.
Deeper Levels of Processing, Elaboration, and Metacomprehension

Metacomprehension and learning are impacted by a number of factors. One prevalent phenomenon in the theories behind learning is deeper levels of information processing. Specifically, numerous studies have shown that a focus on meaning in learning leads to improved recall (e.g., Craik & Lockhart, 1972; Elias & Perfetti, 1973; Jacoby & Craik, 1979; Till & Jenkins, 1973). Whereas short-term memory requires constant attention and verbal rehearsal (mostly phonemic in format, although this can also be semantic and visual), long-term memory (LTM) is mainly semantic (Craik & Lockhart, 1972). Information enters LTM primarily through verbal rehearsal and is organized by meaning. In other words, contrary to rehearsal itself contributing to learning, as posed by the Atkinson-Shiffrin (1968) model, Craik and Lockhart’s theory emphasized that learning through rehearsal occurred when deeper processing and the assignment of meaning took place (also supported by research from Craik & Watkins, 1973, Craik & Tulving, 1975, and Hyde & Jenkins, 1969).

In addition, the more the meaning of a stimulus is elaborated, the better the memory. Learners can connect new information to existing knowledge through elaboration by means of clarifying, adding details, explaining relationships between concepts, using an analogy, making inferences, or visualizing a related image (King, 1992). Furthermore, Anderson and Reder (1979) emphasized that differences in memory code are dependent on the type and amount of elaboration given to that information. Information and all related elaborations are encoded into the cognitive network, which is composed of propositions connecting concepts. Elaboration enhances memory encoding
by creating alternative cognitive pathways and by inference-making. Therefore, recall tends to be highest in related situations, and people typically exhibit the greatest success in elaborating in areas that are most familiar to them. Anderson and Reder further explained that people find it useful to associate meaning to things, and as such, semantic elaboration is preferred to elaborating at phonemic or structural levels. Semantic elaboration is supported when information is presented in richer contexts. Likewise, in their study on sentence complexity, Craik and Tulving (1975) showed that elaboration led to stronger memory codes and improved recall. They demonstrated that the elaboration is required to be consistent and relevant to the word’s meaning. Furthermore, recall was found to be significantly better for highly elaborated integrated memory traces, than for small, unelaborated ones or large poorly elaborated ones (Bradshaw & Anderson, 1982).

Stein and Bransford (1979) added that elaboration, to be most useful, should be ‘precise’. In other words, it should expand on the concept’s relevance to the context. Similarly, elaboration can assist in distinctiveness; a necessary factor for accurate memory codes. By describing features and characteristics that assist in differentiating items and concepts from each other, this form of elaboration can assist in crystallizing memory codes (Eysenck, 1979). In sum, levels of processing and elaboration theories suggest that deep semantic processing of information will lead to more robust learning.

Understandably, deeper levels of processing and elaboration theories have shown to have an impact on metacognitive and metacomprehension processes. Koriat, Lichtenstein, and Fischhoff (1980) found improvements in self-assessment of performance when learners were asked to provide a rationale as to why their answers to general knowledge questions might be both correct and incorrect. Results indicated that
the process of writing these contradictory reasons was the greatest contribution to the learner’s ability to self-assess the accuracy of his/her answers. Maki (1998) theorized that the reasons behind the improved self-assessment observed in the Koriat et al. (1980) study may be attributed to an individual being forced to evaluate their memory of the text and consequently, in doing so, increasing the processing of the material. In addition, in a study of the contribution of explicit feedback to metacognitive knowledge, Melot (1998) found that only participants who re-elaborated on information developed more permanent metacognitive knowledge. Also, cognitive re-elaboration was found to be important in whether the attained metacognitive knowledge had an impact on future behavior. In fact, prior metacognitive knowledge is significant in a learner’s ability to efficiently integrate new metacognitive knowledge through re-elaboration. Finally, Hess (1997) reported that deeper-level study, versus surface-level study, leads to higher academic success, reading comprehension, and levels of metacomprehension. Thus, training techniques fostering deeper information processing are likely to lead to improved metacognition and, specifically, metacomprehension.

In turn, as studies have shown, metacomprehension positively impacts learning, and deeper levels of processing positively impact metacomprehension, making the development of training techniques that encourage deeper levels of information processing critical to the learning process. One such technique assessed the use of guided questions, or ‘question stems,’ as facilitators to the mental elaboration of instructional content (King, 1992). The questions were in either open-ended or fill-in-the-blank format and were content free, allowing learners to generate their own questions, and thus their own elaborations. Elaborations provided by external sources, such as instructors or text-
based elaborations, contributed less to learning than those that were self-generated (e.g., Pressley, McDaniel, Turnure, Wood, & Ahmad, 1987). King suggests this occurs because learners’ own elaborations are likely more aligned with their own knowledge base. She contends that by having to create high-level questions on the training material, learners are pressed to identify main ideas and their relationships to each other and to existing knowledge. In addition, King suggests that learners will likely think about the material in numerous ways, developing new cognitive pathways. The enhanced cognitive representation facilitates comprehension and recall. Another important factor explored in the King study is the concept of student autonomy. Learners having control over their learning has been shown to contribute to intrinsic motivation and achievement (e.g., Deci & Ryan, 1985; King, 1983), and presumably self-regulated learning (King, 1992). In fact, King (1992) found that a guided question strategy, based on question prompts generating elaboration and critical-thinking and a high level of learner autonomy, facilitated self-monitoring of understanding and increased learning. The approach was based on Bloom’s (1956) taxonomy of thinking, emphasizing application, analysis, and evaluation, and focused on stimulating critical thinking. Examples of the question stems include “What would happen if…,” “Explain why …,” and “How does … effect …?” (p. 113). In addition, greater comprehension and retention of the training material was found. King (1989; 1992) and colleagues (King & Rosenshine, 1993) showed that guided questions strategies led to improvements in knowledge structures, metacognitive processes, and strategy use beyond those found through other learning strategies such as summarizing and note taking.
Although the contributions of King’s guided self-questioning approach are clear, a limitation exits in that learners may not strive to cover material beyond a limited scope. Studies suggest that unless prompted, learners rarely use elaboration, especially with expository information (Britton, Van Dusen, Glynn, & Hemphill, 1990). Thus, a technique that provides learners autonomy, while ensuring that instructional content is fully examined, is needed. Notwithstanding, a meta-analysis by Rosenshine, Meister, and Chapman (1996) found that learners presented with questions forcing them to examine their knowledge at various points of an instructional sequence, exhibited large increases in comprehension. They discovered that although these questions were aimed at encouraging conscious engagement with the instructional material, they also inevitably led learners to analyze the state of their knowledge. Keleman and Weaver (1997) also support prompting learners regarding their instructional material, but suggest delaying the questioning for a short time, so that learners have an opportunity to evaluate their current knowledge. Yet, it could be argued that it is the questioning or prompting that raises “learners’ awareness about the current state of knowledge” (Brown & Ford, 2002, p. 217).

These studies have shown the integral relationship between deeper level of processing, metacomprehension, and learning. More so, they point out the importance of training techniques that would encourage deeper and more critical thinking.
Another principal method for advancing learning is through the strengthening of knowledge structures and, consequently, mental model development. The manner in which knowledge is organized and stored in memory has been argued as being equally, if not more, important than the type or amount of knowledge acquired (Chase & Simon, 1973; Johnson-Laird, 1989; Kraiger, Ford, & Salas, 1993; Rouse & Morris, 1986). Likewise, it is commonly accepted that mental models and metacognitive processes impact learning. In fact, researchers maintain that the two primary factors in skill development and problem-solving ability are mental model quality and executive control processes, such as metacognition related abilities (Gott, Lajoie, & Lesgold, 1991). The ability to successfully develop an accurate mental model and self regulate learning and understanding provides experts the ability to distinguish between the effectiveness of alternative procedures and to respond to varying conditions. In other words, expert level knowledge structures allow higher order organization of information (Markman, 1981). In turn, strategic alternatives become closely associated with their applicable conditions (Gott et al., 1991), thus, improving the probability of an effective response to a given situation. Ultimately, more accurate and precise decision making emerges.

Because of their central role in learning and thinking, it is important to understand knowledge structures and mental models. Knowledge structures are at the core of many cognitive processes. They are a representation of one’s knowledge, including the meaning of domain-specific concepts and how those concepts are interrelated (Jonassen,
Beissner, & Yacci, 1993). The integration of concepts provides the basis of information used to determine under what situations the knowledge is applicable (Baxter, Elder, & Glaser, 1996). Diekhoff (1983) describes structural knowledge as knowledge of how domain related concepts are integrated. It is further defined as providing the ‘why’ information behind the interconnections of these concepts and facilitates the conversion of declarative knowledge into applicable procedural knowledge (Jonassen et al., 1993).

With the transition from novice to expertise, knowledge structures develop in their complexity and integration of information; advancing the “structuredness, coherence, and accessibility to interrelated chunks of knowledge” (Glaser, 1989, p. 272). The importance of knowledge structures is further illustrated by their critical role in problem solving (Chi & Glaser, 1985; Gordon & Gill, 1989; Robertson, 1990) and complex decision making (e.g., Nichols, Chipman, & Brennan, 1995). Knowledge structures are described as the foundation of one’s internal mental representations, or mental models. Where knowledge structures form the larger memory base, mental models are the representation of knowledge that is specific to a situation or task. Accordingly, mental models are defined as “specific knowledge structures that are constructed to represent a new situation through the use of generic knowledge of space, time, causality and human intentionality” (Brewer, 1987, p.189). Indeed, Craik (as cited in Johnson-Laird, 1983) first established the basis of mental model theory by describing the concept of “thinking” as the process of manipulating internal representations of experiences, occurrences, or concepts. Dutke (1996), in discussing schemata, described them as “…abstract, long-term, stored knowledge structures which guide the construction
and reconstruction of mental models of situations described in texts” (p. 35). Clearly, an impact on one’s knowledge structure directly influences one’s mental model of a domain.

The vital role knowledge structures and mental models play in comprehension is evident in the theories underlying language comprehension, which utilize a three level structure (Johnson-Laird, 1980, 1983; Kintsch, 1988; van Dijk & Kintsch, 1983). The three levels are a phonemic level; a propositional level, (e.g., where a proposition is the logical linking together of two concepts); and, a third level that leads to mental model development. These levels are integral to meaningful learning, as they form the basis of cognitive structure (Novak & Gowin, 1984; Jonassen, Reeves, Hong, Harvey, & Peters, 1997). Propositions echo the degree to which concepts are related to one another. As learners assign meaning to concepts, they are then able to more accurately integrate multiple concepts with each other. Consequently, the mental model becomes more clearly defined. Gyselinck and Tardieu, (1999) argue that as comprehension occurs, “…the mental model is updated by adding, deleting and changing the locations of the representational elements” (p. 213). They further suggest that, as new information is introduced, mental models are amended through revision, relocation, combining or parsing of the previous and new representational elements; a process that leads to new inferences. Kintsch and van Dijk (1978) emphasized the importance of continuously examining one’s understanding by reviewing material and drawing new inferences. In sum, training techniques that encourage the re-examination of existing knowledge and the accuracy of one’s conclusions strengthen the quality of mental models.

Research has examined the effect of various training manipulations on knowledge structures and mental models. Studies on note taking, which encourage learners to
summarize, organize and elaborate on relevant information, indicate this process facilitates meaningful learning. For example, learners who took notes tended to have higher recall, even though they were not allowed to review their notes (Di Vesta & Gray, 1972). The authors suggested that notes function as a form of ‘external storage.’ This view was supported by Carter and Van Matre (1975), who found that students performed better when having a chance to review their notes, versus those who did not.

Explanations exist as to why note-taking positively influences knowledge structures. Peper and Mayer (1978) assert that if information is actively processed by organizing, paraphrasing, and elaborating on the material, then note taking will facilitate meaningful learning and performance. Barnett, Di Vesta, and Rogozinski (1981) also suggest that processes of rehearsing material and elaboration, where information is integrated into the knowledge structure, may be involved in the recording and the successful use of notes.

In another line of research, Cuevas, Fiore, and Oser (2002) used diagrams in training material to foster in the development of knowledge structures and mental models. The authors defined mental models as a subset of knowledge structures. In another study, using the theory that expert knowledge on a topic is created by strengthened connections between concepts (e.g., Glaser, 1989), Fiore, Cuevas, and Oser, (2003) investigated the use of diagrams embedded in training material as a means of facilitating these connections. They argued that as mental models can be defined as organized memory structures reflecting one’s comprehension of an issue (e.g., Johnson-Laird, 1983; Klimoski & Mohammed, 1994; Rouse, Cannon-Bowers, & Salas, 1992), diagrams are external representations of textual information; which in turn, assist in related mental model development (Gyselinck & Tardieu, 1999). In fact, Fiore et al.,
(2003) found that the presence of diagrams in training materials assisted in more accurate conclusions by learners across training modules and in performance on integrative knowledge performance. The same was not found for declarative knowledge, however.

Similarly, in an effort to find effective learning techniques, Chi (2000) explored the notion of self-explaining in understanding new information. Chi discusses “the self-explanation (SE) effect,” as linking constructive activity to knowledge reorganization, including revising one’s mental representations or knowledge structures. Chi argued that self-explaining leads to dual processes: 1) generating inferences, and 2) revising one’s mental representations or knowledge structures. Chi suggested that inference making assists in both degree and depth of learning and in answering difficult ‘why’ questions and considered inference making as contributing to the advancement of cognitive representations. The assumption is that inferences complete mental representations and, consequently, lead to improved learning. Study results supported this assumption, as demonstrated by the superior performance of high explainers. The author also maintains that the contribution of the inference-making process to self-explaining is evident in research showing high explainers as more successful at inductive reasoning, despite omissions in the presented text (also supported by Chi, de Leeuw, Chiu, & LaVancher, 1994). However, Chi argues that inference making cannot be the only process behind the impact of the self-explaining effect on comprehension and learning stemming. Specifically, Chi states that the inference-making process alone does not explain the variations in learners’ use of explanation inferences observed in learners. Beyond elaboration for memorization, self-explaining invokes a mechanism for making sense of the information specific to the learner. As such, the author asserts that a second process is
present in the self-explaining effect: one, beyond inference making, requiring greater introspection and analysis. Thus, it is suggested that the results from the self-explaining effect are based on a dual-process phenomenon that includes the repairing of mental models. It is presumed that learners have preconceived or ‘preliminary’ mental models as they approach a learning situation. These mental models are likely incorrect or incomplete. Thus, Chi postulates that self-explaining facilitates the revision of existing mental models. The process of self-explaining is used by learners to make inferences that pertain to their specific comprehension deficiencies, in turn, allowing the learners to amend their mental representations. In fact, Chi argues, it is the imperfections in mental models that lead to greatest learning. In other words, the existence of knowledge gaps or misconceptions primarily become evident when, in the process of self-explaining and integrating new information, learners realize that there is a conflict, violation, omission, or contradiction in their current understanding. Once having detected insufficiencies in comprehension, learners typically begin self-explaining behavior in an effort to improve understanding (e.g. Chi, Bassok, Lewis, Reimann, & Glaser, 1989). Finally, Chi adds that self-explanation is also useful in augmenting instruction, since instructors are not likely to accurately assess each learner’s mental model nor are able to provide elaborations to fit all learner needs. Learners are not likely to detect all knowledge errors, however. As such, training approaches seeking to capitalize on the self-explanation effect should include methods that would encourage learners to examine their understanding against all the instructional material.

In sum, research supports that learning is optimal when learners invoke a process in which the learner is assisted in correcting misperceptions and strengthening accurate
connections between concepts. As an individual’s skill level moves from novice to expert, knowledge structures are reinforced, mental models are elaborated, and the connection between the given conditions and choice of strategic function are increasingly clear and automated (Gott, Lajoie, & Lesgold, 1991). This progression toward expertise parallels Anderson’s theory of skill acquisition (1982), which states that knowledge acquisition is done in three levels: declarative knowledge; more automatic, procedural knowledge; and, knowledge that is transferable, through increased flexibility and specificity, to various situations.

Concept Maps and Learning

In a search for effective interventions toward learning, and armed with the knowledge of the integral role that mental model development plays in learning, some researchers have focused on the use of concept maps as teaching tools. The fundamental theory behind concept mapping is the semantic networking theory, which states that memory is composed of schemas (i.e. ideas) that are interrelated based on meaning (semantically). The network they create is referred to as a semantic network (Quillian, 1968). As representations of cognitive networks, concept maps have had various roles in the instructional process, including, as a strategy for curriculum planning, instructional, learning, and assessment (Novak, 1990). Researchers have also used concept map development as an assessment tool to glimpse into learners’ internal mental models (e.g., Rice, Ryan, & Samson, 1998). Additional applications of concept maps include using the
maps as a strategy for curriculum development (Jonassen, 1991; Wang & Rada, 1995), so that course content is coherent and logically linked. Others (Jonassen, Reeves, Hong, Harvey, Peters, 1997) have studied the benefits of using concept maps as advanced organizers of forthcoming information. Furthermore, they have been used as teaching tools, where the instructor or learners develop them together as they work through instructional material. Finally, concept maps are used by instructional designers as task analysis tools (Jonassen et al., 1997).

Techniques often used for eliciting knowledge structures in order to create concept maps include free recall, sorting or ordering, and question probe (Moore & Gordon, 1988). During free recall, an individual is asked to discuss all that is known about a topic and a translator transcribes what is being explained. With sorting and ordering methods, individuals sort concepts based on their associations with each other. Both these techniques, however, may leave out information pertaining to the type of relationships that exist between the concepts. During the question probe method, individuals are asked to read a passage of text and then asked questions aimed at drawing out the ‘how, what, when, where, who, and why’ information from the text. This information can then be used to generate a concept map. These techniques can have assessment, as well as, instructional applications. For instance, Gordon, Gill, and Moore (1988) used the question probe technique to generate an expert concept model for instructional and assessment purposes. The question probe technique has also been used to evaluate two separate instructional approaches (Gill, Gordon, Moore, & Barbera, 1988). Similarly, the Fill-in-the-Structure (FITS) technique by Naveh-Benjamin and Lin (1995) also was found to provide cognitive structure information. Student using FITS are
given incomplete graphic hierarchical representation of the instructional material, and then using listed concepts from the training, students completed the graphic. The results were used to assess students’ cognitive structure and its development throughout a course.

Concept maps as advanced organizers are largely viewed as beneficial. In fact some argue that they are necessary part of learners being able to assess their learning (Cates, 1992; Park & Hannafin, 1993). A number of authors have recommended the use of concept maps to improve instruction and learning in various areas including chemistry (Novak, 1984), literature and physics (Moreira, 1985), reading (Gold, 1984), social studies (Wease, 1986), ecology, and computer-based instruction (Heinze-Fry, Crovello, & Novak, 1984). For example, Hirumi and Bowers (1991) studied the use of graphic concept trees coupled with instructional text, finding that graphical representations of the text-based instructions led to higher performance and improvements in confidence, attention, motivation, and satisfaction toward the training material. Additionally, improvements were found in recall regarding identifying and defining concepts and the hierarchical relationships between them. Meta-analytical studies support these findings (Kozlow, 1978; Luiten, Ames, & Ackerman, 1980; Mayer, 1979; Stone, 1983).

Willerman and Mac Harg (1991) also demonstrated the effectiveness of using concept maps as advanced organizers in the classroom. Blank concepts maps were provided to the experimental group and students were asked to complete the concept map by copying the teacher’s version. Results indicated the experimental group’s academic performance was significantly higher than students not using concept maps. Other research showed that graphical organizers improved learning, regardless of the training domain (Moore &
Readance, 1984). However, they also determined that, although more time consuming, postorganizers (graphic organizers created after the learning task by either the instructor or the student) had a significantly greater impact on learning than graphic organizers created in advance.

Hence, a small number of researchers have focused beyond concept maps as advanced organizers and on learner-generated concept mapping to facilitate learning. According to Long (1976), Holley and Dansereau were one of the first to test the use of learner-generated concept models as learning tools. Their ‘networking’ learning strategy placed emphasis on assisting students “in spatially reorganizing passage information as part of the encoding process” (Holley & Dansereau, 1984, p. 86). After several adaptations to the methodology, learners were provided with three structure types (hierarchies, chains, and clusters) and six related link options (under ‘hierarchies’ the links included ‘part of’ and ‘type of’; under ‘chain’ the link was ‘leads to’; and under ‘cluster’ the links were ‘analogy’, ‘characteristic’, and ‘evidence’) to develop their concept networks (Holley, Dansereau, McDonald, Garland, & Collins, 1979).

In addition, based on Ausubel’s (1968) assimilation theory of cognitive learning that states that meaningful learning stems from the linking of new information to existing knowledge, Novak (1977, 1979, 1980, 1981) developed the idea of the hierarchical representations, eventually known as ‘cognitive maps’ and ‘concept maps’. He later studied the use of concept maps as learning and teaching tools (Heinze-Fry & Novak, 1989; Novak, Gowin, & Johansen, 1983). Similar techniques of concept map building by learners have been used primarily in science classrooms. For example, biology students using concept mapping showed improvements in standardized achievement tests (Jegede,
Alaiyemola, & Okebukola, 1990). In fact, Okebukola et al. (1993) found that students familiar with concept mapping often drew a concept map, when faced with a problem solving task, and tended to be more decisive as to a course of action. The authors suggest that this is a reflection of increased attention to, and understanding of, directions. In a physical therapy education setting, concept mapping was also shown to increase one’s ability to apply acquired knowledge to problem solving (Beissner, 1992). Finally, Jonassen (1993) found that the construction of concept maps as a study method led to improvements in consistency and understanding of hierarchical relationships and knowledge structures. Overall, in the process of creating concept maps of instructional material, learners may be repeatedly revising their interpretation of the text by posing new propositions as they elaborate on and refine the information. These processes and the creation of cross-links, connecting concepts between different domains, solidify the concepts into the knowledge structure, add to the knowledge base, and support pattern and relationship recognition (Jonassen, Reeves, Hong, Harvey, & Peters, 1997).

To summarize, although concept maps functioning as advanced organizers are certainly beneficial, it would seem that the benefits of forcing a learner to examine and amend the current state of their knowledge through concept model development would prove more effective for learning. Advanced organizers do little to challenge the accuracy of the learners’ understanding of their learning. In other words, learners looking at a concept model of the training material may feel assured that they have a thorough understanding of it. Only when they are forced to create a representation of the material are the gaps and misperceptions in their knowledge base revealed. In short, it may be that advanced organizers rely on recognition, whereas concept model
development requires recalling and understanding ‘how’ and ‘why’ the interrelationships between concepts exist. If concept map development fosters improved metacomprehension, which in turn improves knowledge deficiencies and misunderstandings, then concept map development should enhance learning.

**Hypotheses**

As illustrated in previous sections, mental model development, deeper levels of information processing, and elaboration are critical to learning. Additionally, individuals’ metacomprehension accuracy is integral to making improvements to their knowledge base. In other words, without an accurate perception of the depth of their knowledge on a topic, learners may not know that knowledge gaps or misperceptions exist and, in turn, would be less likely to correct them. Therefore, this study offered a dual-process approach that aimed at enhancing metacomprehension. One path aimed at advancing knowledge structure development and, thus, mental model development. The other focused on promoting a deeper level of information processing, through processes like elaboration. This dual approach was predicted to culminate in improved metacomprehension and increased learning.

Accordingly, the role of learner-generated concept model development in facilitating metacomprehension and knowledge acquisition was examined. Although the technique of concept mapping by learners has been repeatedly and successfully used to test mental models, the present study tested if concept model building could also be used as an effective training tool. The Graduated Concept Model Development (GCMD)
technique employed in this study was based on the theory that knowledge acquisition would improve when learners integrate new information into existing knowledge, correct misperceptions, close knowledge gaps, and strengthen accurate connections between concepts by posing targeted questions against their existing knowledge structures. Furthermore, this study emphasized meaningful learning and suggested a process by which newly introduced concepts would be manipulated for the purpose of improving metacomprehension via strengthening accurate knowledge structures and mental model development, and through deeper and elaborated information processing. The predicted benefits of the GCMD technique for knowledge acquisition were also based on the levels of processing theory (e.g., Craik & Lockhart, 1972; Craik & Tulving, 1975) in that the deeper items are processed during the development of a concept map, the more likely they will be remembered. Since learners would be encouraged to manipulate the concepts in an effort to correctly organize them in the model, they would, as a result, be required to assign meaning to the concepts, processing them at a deeper semantic level, elaborate and find distinctions between them, and, thus, somewhat inadvertently reinforcing them into memory.

Specifically, it was hypothesized that through the process of the GCMD technique, the learner would more accurately integrate new concepts into their knowledge base. This mechanism encourages learners, as they work through training material, to build a concept model depicting the relationship between key concepts. As a result, the learners would be continuously recalling, retesting, and actively integrating knowledge. The hypothesis was that if learners developed concept models during a training session and thus, manipulated concepts to a larger and deeper degree, metacomprehension would
improve and learning would increase. The Figure 1 depicts the hypothesis behind this study.

Figure 1: Conceptual overview of the hypothesized effect of the Graduated Concept Model Development (GCMD) on learning outcomes.

As mentioned, the GCMD technique focuses on the process of a learner building a concept model of baseline knowledge of a topic, becoming introduced to new related concepts, then challenging and integrating the new concepts into the previous concept model. As learners incorporate new knowledge and build concept models, their knowledge structures of the training material develops. These knowledge structures become the basis of learners’ mental models of the training concepts. Likewise, in
developing the concept models, new and existing knowledge is more deeply analyzed through elaboration and distinguished from similar concepts and assigned meaning. Both these co-existing processes may provide the information necessary for accurate metacomprehension. The more accurate the learners’ assessment of their understanding, the more easily they can identify gaps or errors in logic. This larger process occurs in an iterative cycle. The goal is to increase metacomprehension and, in turn, learning, demonstrated through improved test performance on knowledge of concepts and the relationships between them.

In the past, the technique of linking concepts together has been used to test mental models; however, this study proposed that this technique can be used as a training tool. Consequently, a series of hypotheses were established in three areas: mental model accuracy, metacomprehension accuracy, and knowledge acquisition.

**Mental Model Accuracy Hypotheses.** These hypotheses refer to the degree to which concept maps may facilitate participants’ mental model development, as indicated by greater similarity to an expert model.

H₁: Overall, participants building their own concept maps (with or without feedback) were predicted to show greater similarity to an expert model, than participants not using concept maps (i.e., control group) or those using a concept map as an advanced organizer.
H₂: Participants building their own concept maps with feedback were predicted to show greater similarity to an expert model, than participants building their own concept maps with no feedback.

H₃: Participants using a concept map as an advanced organizer were predicted to show greater similarity to the expert model, than participants not using concept maps (i.e., control group).

Metacomprehension Accuracy Hypotheses. These hypotheses refer to the degree to which concept maps may facilitate participants’ metacomprehension accuracy, as measured by comparing participants’ self-judgments of performance with actual performance.

H₄: Overall, participants building their own concept maps (with or without feedback) were predicted to display greater metacomprehension accuracy, than participants not using concept maps (i.e., control group) or those using a concept map as an advanced organizer.

H₅: Participants building their own concept maps with feedback were predicted to display greater metacomprehension accuracy, than participants building their own concept maps with no feedback.
H₆: Participants using a concept map as an *advanced organizer* were predicted to display greater metacomprehension accuracy, than participants *not* using concept maps (i.e., control group).

*Knowledge Acquisition Hypotheses.* These hypotheses refer to the degree to which concept maps may facilitate participants’ knowledge acquisition.

H₇: Overall, participants *building* their own concept maps (with or without feedback) were predicted to perform better on assessment of *integrative* knowledge (i.e., integration and application of task-relevant concepts) than participants *not* using concept maps or those using a concept map as an *advanced organizer*.

H₈: Participants building their own concept maps with *feedback* were predicted to perform better on assessment of *integrative* knowledge (i.e., integration and application of task-relevant concepts) than participants building their own concept maps with *no feedback*.

H₉: Participants using a concept map as an *advanced organizer* were predicted to perform better on assessment of *integrative* knowledge (i.e., integration and application of task-relevant concepts) than participants *not* using concept maps.
$H_{10}$: Consistent with prior research (e.g., Cuevas et al., 2002; Fiore et al., 2003), no significant differences in performance were predicted for assessment of *declarative* knowledge (i.e., mastery of basic factual information).
METHOD

Participants

Participants were 68 (34 female, 34 male, ages 18-35, mean age = 21.43) undergraduate students from a major southeastern university. This sample had an average grade point average (GPA) of 3.46 and a mean total Scholastic Aptitude Test (SAT) score of 1157.44. Participants were randomly assigned to one of the four experimental conditions, and subsequent analyses revealed no significant differences between the groups on GPA and SAT scores. Participants received course credit or monetary compensation for their efforts and participation was available to all students. In addition, being that data collection fell primarily between semesters, during which class research credit was unavailable, students were offered the opportunity to win prizes (Apple iPod 20GB MP3 player, generic brand MP3 player, or “jump drive” portable universal serial bus [USB] storage devices) for the top performance on the Knowledge Assessment Test as incentive for participation. Ties were broken using the result from the card sort task. The ethical standards of the American Psychological Association (APA) regarding the treatment of participants were strictly followed.
Design

This study used a one-way, between-groups design with concept map type serving as the independent variable with four levels: no concept map (control condition), concept map as an advanced organizer (advanced organizer condition), learner-built concept map with feedback (feedback condition), and learner-built concept map without feedback (graduated concept map development, or GCMD, condition). The dependent variables included performance (percent correct) on a declarative and integrative knowledge assessment test, mental model development, and metacomprehension accuracy.

Materials

Distributed Dynamic Decision-Making Tutorial

The tutorial utilized was based on the Distributed Dynamic Decision-Making (DDD) model: a simulated military command and control environment aimed at creating events to encourage team coordination and performance (for a detailed description, see Kleinman & Serfaty, 1989). Although for the purposes of this study participants were asked to interact with the tutorial only and not the simulated environment, the components of the simulation were briefly described to the participants. In general, the simulation would require three team members (decision makers) to coordinate actions and resources in protecting four sectors from enemy attack. Team members would be
responsible for protecting their sectors, via assets such as jets and tanks, and for supporting the team in successfully protecting the entire area. The team’s performance, processing, and functioning are used as measures. To successfully accomplish their goal, trainees have to, as in a real-world setting, process various knowledge types, including declarative, strategic, and integrative knowledge (see Fiore et al., 2002).

The DDD game’s tutorial is composed of two modules presented in an interactive Microsoft PowerPoint format. The multimedia based tutorial is hierarchically organized within both modules. The first module focuses on basic declarative instruction on the necessary concepts for learning how to play the DDD game, such as scoring, rules of engagement, assets, targets, and the playing area. The second module provides strategic instruction on optimal strategies to perform well in the DDD game, such as how to maximize use of resources. The strategic instruction module also offers multimedia (i.e., audio-video-interleaved files) demonstrations of these strategies during actual DDD scenarios. Hyperlinks within the tutorial provided additional information on concepts presented. Participants were able to work at their own pace.

**Experimental Conditions**

Below is a description of the four experimental conditions created for this experiment.

*Control.* Participants in the control condition only worked through the DDD Microsoft PowerPoint-based tutorial, that is, no concept map was provided nor did participants build a concept map during their training.
**Advanced Organizer.** Participants in this condition also worked through the DDD tutorial, however they were also provided with a completed concept map, as an advanced organizer, depicting the content of the DDD training material, to refer to when reading. In addition, participants in this condition were asked to continue to study the DDD tutorial and related material. The task completion time of the concept mapping conditions is likely much longer, than in the advanced organizer condition. To balance this difference, participants in the advanced organizer condition were given DDD tutorial related material to read for the average length of time estimated to complete the learner generated concept map condition. Specifically, participants were asked to study the DDD tutorial review for 45 min.

**Feedback.** Participants in the third condition also worked through the DDD tutorial. In doing so, they were asked to generate their own concept map depicting the primary concepts and interrelationships described in the training material. As participants worked through both modules of the tutorial, they were asked to stop in graduated amounts, at previously determined points, to initially create, and then add to and revise their concept map. In other words, participants worked through the tutorial, stopped periodically, reviewed the tutorial as they deemed necessary, and then returned to their concept map and integrated new knowledge. They were asked to challenge and rework their existing concept map as new information changed their understanding of the training material.

The amount of times participants revised their concept model was left to their discretion. Participants repeated this process until they had completed both modules of the training material and incorporated all the relevant concepts and relationships into their
concept model. After the participants had completed their concept map, the percent correct feedback, as compared to an expert model, was calculated and reported to them. Participants were free to review all prior sections of the tutorial material and update their concept map accordingly in the following section of the tutorial. Additionally, this condition provided feedback to the learner, based on the theory that feedback is a necessary part of accurate mental model development and learning (Eberts, 1994; Norman 1983).

**GCMD.** Participants in the fourth condition ran through the study in the same manner as in condition three, but were not given feedback on their concept map, as it compared to the expert model. In contrast to the feedback condition, this condition focused on testing GCMD directly, minus external feedback as part of the intervention. It allows the examination of the effect of GCMD on learning separate from the presence of feedback. Plus, it eliminates the question of whether feedback may lead to more trial-and-error behavior versus hypothesis testing.

**Concept Map Development**

Concept map building by learners or research participants have traditionally been completed by hand. This is often a very laborious task for those building the concept map. Often, they are required to redraw the concept map several times before its finalization. The resulting figure may be difficult to read and interpret during analysis, thus making the technique prone to errors. Therefore, the TPL-KATS – concept map software tool (Team Performance Laboratory - Knowledge Assessment Tool Suite) was
used by participants in the two learner-built concept map condition of this study (i.e., the
feedback and GCMD conditions). The use of a computerized method of concept map
building has not shown to change the effectiveness of the concept model building task
itself (Harper, Evans, Dew, Jentsch, & Bowers, 2002). The TPL-KATS – concept map is
comprised of three modes; the experiment mode, the administrative mode, and the
terminal mode. Users of the tool primarily create concept maps in the experiment mode
(Hoef, Jentsch, Harper, Evans, Bowers, & Salas, 2003). The software interface has three
primary elements; the concept list, the proposition list, and the board. The concepts to be
added to the concept map are placed within the concept list window. In general, these
concepts may be added by the administrator of the test or by the participant.

For the purposes of this study, a list of primary concepts from the training
material was made available to participants in the two experimental conditions that built
their own concept maps: feedback and GCMD. Participants were allowed to add
additional concepts to the concept list as they proceeded through the training material. A
proposition explains how one concept is related to another. The proposition list may also
be generated by the administrator or by the participant; however, in this study a set of
propositions were available for the participants. Participants were not limited to the listed
propositions and were free to add additional ones, as they deemed necessary. Finally, a
board, or desktop work area, was provided, where users of the tool could place concepts
and link them together. Items on the board could be easily moved about with a drag-and-
drop motion. TPL-KATS – concept map was not, however, used as a measure during the
study, only as a tool for concept map development. Participants of the two concept
mapping conditions went through a Microsoft PowerPoint instructional tutorial on the TPL-KATS – concept map software just prior to beginning the DDD tutorial.

**Metacomprehension Accuracy**

Upon completion of each module in the tutorial, participants were asked to predict (metacomprehension prediction) how well they would do on multiple-choice questions on the concepts presented in the respective module. Responses were recorded on a 10-point scale, from 0 to 100%, in 10% increments. Similarly, following completion of the knowledge assessment task (described in a later section), participants were asked to postdict (metacomprehension postdiction) how well they did on the knowledge assessment task overall, as well as on the individual sections (i.e., declarative and integrative), using the same method described previously. The differences between each participant’s prediction and postdiction of performance with their actual performance were calculated to determine the accuracy of the participants’ self-assessments, thus, indicating the level to which participants were able to scrutinize the level of their understanding of the complex task (see Maki, 1998). Specifically, in this study metacomprehension accuracy was measured by self-reported level of understanding and by prediction of future performance and postdiction of actual performance as correlated with actual performance on a Knowledge Assessment Test.
Knowledge Assessment Test

Participants’ knowledge acquisition was assessed using two distinct types of multiple-choice questions: declarative and integrative. The declarative knowledge assessment section consisted of 15 questions that assessed participants’ mastery of basic factual information provided by the training. The integrative knowledge assessment section consisted of 10 questions that assessed participants’ ability to integrate the concepts and knowledge gained from the training and the ability to transfer that knowledge to a novel task. These consisted of simulation vignettes of the DDD game (see Fiore et al. 2002 for a description).

Mental Model Assessment – Card Sort Task

Currently, there are a few measures for mental model assessment. The primary three available include card sorting, concept mapping, and pairwise relatedness rating using Pathfinder software. A study by Evans, Jentsch, Hitt, Bowers, and Salas (2001) comparing these three types of assessment found that although the strongest correlation exists between card sorting and concept mapping, it is merely .128. This finding likely indicates that each assessment type is measuring a different type of knowledge. For the purposes of this study, however, card-sorting was used as the measure for mental model development, instead of concept mapping, for two reasons. First, concept mapping is used as an intervention, so it may give participants in those conditions an advantage. Second, results may inadvertently be a reflection of participants’ memory of the created
(GCMD condition) or reviewed (advanced organizer condition) concept map, versus mental model development, as compared to an expert model.

Card sorting tasks have shown to provide a glimpse into how people perceive the relationships between concepts (Fiore et al., 2003; Jonassen, Beissner, & Yacci, 1993). In other words, the resultant organization from a card sorting task is a reflection of one’s knowledge structure and mental model of the training material. Typically, card sorting tasks have been conducted manually. To improve the efficiency of administrating and analyzing results, a computer based card sorting tool is preferred. The TPL-KATS (Team Performance Laboratory - Knowledge Assessment Tool Suite) (Copyright 2001, Team Performance Laboratory, University of Central Florida) card sort software was used to assess participants’ mental model of the training material after completing one of three of the study conditions. The TPL-KATS card sort interface is composed of a card list, pile list, and board. The board makes up the desktop work area. Key concepts from the tutorial were provided via the card lists. As participants went through the exercise of sorting concepts, they were free to create as many pile lists as they found necessary, and label them as they chose. Participants were asked to place each concept into one of the pile lists until all the cards have been sorted. All participants went through a Microsoft PowerPoint instructional tutorial on the TPL-KATS – card sort software just prior to beginning the card sort task.
Self-Efficacy Measure

Self-efficacy is a measure of one’s confidence in his/her ability to be successful at a job or task. Those with higher task self-efficacy have higher confidence in their ability to successfully complete that task. Self-efficacy on one task does not necessarily translate to high self-efficacy on another task. Research has demonstrated that self-efficacy and performance have a positive relationship. In other words, those who are confident in their success tend to succeed more so those who lacking in confidence. A meta-analysis of 13 lab and field studies by Locke and Latham (1990) resulted in a mean correlation of self-efficacy and performance of .39 and a high correlation of .74. As such, an independent measure of self-efficacy (see Appendix C) was administered to evaluate any potential effect of this construct on participants’ metacomprehension accuracy and performance on the knowledge assessment questions.

Apparatus

The DDD tutorial software program, the Knowledge Assessment Test, and the electronic card sorting task were run on an IBM-compatible computer. Both the tutorial and Knowledge Assessment Test were in Microsoft PowerPoint format, interjected with audio-video-interleaved (AVI) multimedia. The TPL-KATS card sorting task was developed using Java programming. Participants were able to navigate through all these
programs via mouse point-and-click. Participant in the feedback and GCMD conditions were asked to use the TPL-KATS – concept map.

**Procedure**

Upon arrival, participants were randomly assigned to one of the four experimental conditions (control, advanced organizer, feedback, or GCMD). Participants then progressed through the three stages of the experiment. In *Stage I*, participants completed forms regarding informed consent (see Appendix A), general biographical information (see Appendix B), and task self-efficacy (see Appendix C). In *Stage II*, participants completed the self-paced tutorial on the DDD game, as previously described. The manner by which they worked through the tutorial was determined by their assigned concept map condition. Upon finishing each module of the tutorial, participants then completed a metacomprehension prediction questionnaire (see Appendix D). In *Stage III*, participants completed the computer-based Knowledge Assessment Test, covering both declarative and integrative knowledge, followed by a Knowledge Assessment Questionnaire (see Appendix E) for metacomprehension postdiction evaluation. Participants then completed the card sort task, as the assessment of mental model development. Finally, participants completed a general study survey and were debriefed as to the purpose of the study. The entire experiment lasted approximately 2 to 3 hr.
RESULTS

The following sections present the statistical analyses and results for the cognitive and metacognitive outcomes. An alpha level of .05 was used for all analyses. Furthermore, to ensure random assignment created four equal groups prior to the experiment with regard to GPA, SAT scores, and self-efficacy, a series of one-way ANOVAs were performed. Results indicated no significant differences between the control, advanced organizer, feedback, and GCMD conditions on: (a) GPA, $F(3, 53) = 1.729, p = .172$; (b) SAT total scores, $F(3, 35) = .079, p = .971$; and (c) self efficacy, $F(3, 64) = 1.163, p = .331$. Note that error degrees of freedom for these analyses are not consistent due to missing data for the GPA and SAT variables.

Cognitive Outcomes

Cognitive performance was evaluated with two primary dependent measures: the accuracy of participants’ mental models, and their performance on the Knowledge Assessment Test. A series of analyses were conducted to determine the effect of condition on mental model accuracy and knowledge assessment performance, as well as the degree of relationship between these two measures.
Mental Model Accuracy

Mental model accuracy (MMA) was calculated as the correlation between a participant’s responses on the TPL-KATS card-sorting task, and the card-sorting responses of a subject matter expert (SME). Accordingly, scores for the MMA dependent measure ranged from -1.0 to 1.0 with larger positive values indicating a more accurate mental model. A one-way between groups Analysis of Variance (ANOVA) was used to compare MMA across the four experimental conditions (control, advanced organizer, feedback, and GCMD). Results revealed no significant differences between the four conditions on MMA, $F(3, 64) = .240, p = .868$, as summarized in Table 1.

Table 1: Mental Model Accuracy Means by Condition

<table>
<thead>
<tr>
<th>Condition</th>
<th>$M$</th>
<th>$SD$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>.383</td>
<td>.158</td>
</tr>
<tr>
<td>Advanced Organizer</td>
<td>.370</td>
<td>.162</td>
</tr>
<tr>
<td>Concept Map w/ Feedback</td>
<td>.368</td>
<td>.140</td>
</tr>
<tr>
<td>GCMD</td>
<td>.342</td>
<td>.117</td>
</tr>
</tbody>
</table>

*Note. Higher, positive scores indicate more accurate mental models.*
Knowledge Assessment

Scores on the two components of the Knowledge Assessment Test (Declarative and Integrative) and Total scores were compared across the four conditions. A one-way MANOVA on the effect of condition on the percent correct for the three measures did not reveal a significant main effect for condition, Wilks’s $\Lambda = .91$, $F(6, 126) = 1.02$, $p = .418$. The partial $\eta^2$ based on Wilks’s $\Lambda$ was small, .046. Table 2 displays means and standard deviations for each condition on the three Knowledge Assessment Test measures.

Table 2: Means and Standard Deviations for the Percent Correct Declarative, Integrative, and Total Knowledge Assessment Test Scores across All Conditions

<table>
<thead>
<tr>
<th>Condition</th>
<th>Declarative</th>
<th>Integrative</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>Control</td>
<td>.835</td>
<td>.149</td>
<td>.735</td>
</tr>
<tr>
<td>Advanced Organizer</td>
<td>.867</td>
<td>.151</td>
<td>.688</td>
</tr>
<tr>
<td>Feedback</td>
<td>.886</td>
<td>.133</td>
<td>.712</td>
</tr>
<tr>
<td>GCMD</td>
<td>.835</td>
<td>.212</td>
<td>.635</td>
</tr>
</tbody>
</table>

*Note.* Higher scores are indicative of better knowledge assessment performance.

Relation between Mental Model Accuracy and Knowledge Assessment Performance

In order to test the effect of MMA on Knowledge Assessment Test performance, participants’ MMA scores across all conditions were split into Low MMA ($n = 32$) and
High MMA groups (n = 32) using a median-split at .372. Next, a series of independent samples $t$ tests were conducted to determine if these two groups differed on Declarative, Integrative, and Total percent correct scores. Table 3 presents descriptive statistics for all three analyses.

Results for the Declarative scores indicated participants in the High MMA group scored significantly higher than participants in the Low MMA group, $t(66) = -2.55, p = .013$. Similarly, with regard to Integrative scores, participants in the High MMA group scored significantly higher than those in the Low MMA group, $t(66) = -2.05, p = .044$. Finally, results for the Total scores indicated the High MMA group exhibited a significantly higher Total percent correct than the Low MMA group, $t(66) = -2.59, p = .012$.

Table 3: Means and Standard Deviations for the Percent Correct Declarative, Integrative, and Total Knowledge Assessment Test Scores for Low and High Mental Model Accuracy Groups

<table>
<thead>
<tr>
<th>MMA Group</th>
<th>Declarative</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
<td>$SD$</td>
</tr>
<tr>
<td>Low MMA</td>
<td>.808</td>
<td>.177</td>
<td>.650</td>
<td>.205</td>
<td>.745</td>
<td>.176</td>
</tr>
<tr>
<td>High MMA</td>
<td>.904</td>
<td>.132</td>
<td>.735</td>
<td>.130</td>
<td>.837</td>
<td>.107</td>
</tr>
</tbody>
</table>

*Note.* Higher scores are indicative of better knowledge assessment performance.
Metacognitive Outcomes

Metacomprehension Accuracy

Metacomprehension accuracy was evaluated two ways based on 1) participants’ level of understanding of the tutorial concepts and their actual performance on the Knowledge Assessment Test, and 2) predictions and postdictions of how well they did on the Knowledge Assessment Test and their actual performance.

Metacomprehension accuracy based on subjectively assessed level of understanding

Metacomprehension accuracy was first assessed as the correlation between participants’ level of understanding of the concepts presented in each of the two DDD Training Tutorial modules (based on responses on the DDD Prediction Survey querying participants’ understanding of the concepts in a given module) and actual performance on the Knowledge Assessment Test. Participant responses to item 3 on the survey, which asked “Overall, what is your level of understanding of the material presented in this module?” based on a 7-point scale (1 = very poor, 7 = very good), were recorded for both modules and subsequently labeled MetaKnowledge M1 and MetaKnowledge M2, respectively. To evaluate metacomprehension accuracy, these two variables were correlated with percent correct scores on the Knowledge Assessment Test (Declarative, Integrative, and Total scores) first overall, and then by condition.
Pearson correlations revealed for all conditions, level of understanding responses after the first module (MetaKnowledge M1) were positively correlated with percent correct scores on the Knowledge Assessment Test for the Declarative, \( r(68) = .428, p < .001 \), Integrative, \( r(68) = .345, p = .004 \), and Total subsections, \( r(68) = .433, p < .001 \).

Smaller but significant positive correlations were also revealed between level of understanding responses after the second module (MetaKnowledge M2) and scores on the Declarative, \( r(68) = .308, p = .011 \), Integrative, \( r(68) = .247, p = .042 \), and Total subsections, \( r(68) = .310, p = .010 \).

Pearson correlations were also conducted between level of understanding responses and the Knowledge Assessment Test scores for each experimental condition. First, for the control condition, the only significant correlations were between responses for the first module (MetaKnowledge M1) and Declarative, \( r(17) = .522, p = .032 \), and Total scores, \( r(17) = .540, p = .025 \). Second, for the advanced organizer condition, there were no significant correlations between the Knowledge Assessment Test scores and level of understanding for both modules. Third, participants in the feedback condition exhibited positive correlations between MetaKnowledge M1 and Integrative, \( r(17) = .606, p = .010 \), and Total test scores \( r(17) = .514, p = .035 \). The feedback condition showed the same pattern for the second module, with MetaKnowledge M2 positively correlated with Integrative, \( r(17) = .613, p = .009 \), and Total test scores \( r(17) = .560, p = .019 \). For the fourth condition, GCMD, there were significant correlations between level of understanding for the first module (MetaKnowledge M1) on Declarative, \( r(17) = .687, p = .002 \), Integrative, \( r(17) = .651, p = .005 \), and Total scores, \( r(17) = .690, p = .002 \), but no
significant correlations for the second module. Results for all four conditions are
summarized in Figure 2.

Figure 2: Pearson Correlations for Metacomprehension Accuracy Based on Level of
Understanding for Modules 1 and 2 across Conditions

Metacomprehension accuracy based on predictions and postdictions of knowledge
assessment performance

Metacomprehension accuracy was also assessed as the degree to which
predictions and postdictions of performance on the Knowledge Assessment Test
correlated with actual performance on the test. Predictions were calculated from
responses to item 4 on the DDD Prediction Survey which asked participants to rate, on an
11-point scale, their anticipated percent correct on the Knowledge Assessment Test.
Prediction scores were gathered after Modules 1 and 2 of the tutorial and labeled MetaPre
M1 and MetaPre M2, respectively. In addition, following administration of the Knowledge Assessment Test, participants were asked to rate their perceived performance on the test overall and for the declarative and integrative subsections. These responses were labeled MetaPost All, MetaPost Declarative, and MetaPost Integrative.

To evaluate metacomprehension accuracy, the five aforementioned variables were correlated with percent correct scores on the Knowledge Assessment Test. Correlations were conducted overall and then for each individual condition. For the overall analysis, participant predictions and postdictions about performance on the Knowledge Assessment Test were positively correlated with actual performance on the test for Declarative, Integrative, and Total percent correct, as shown in Table 4.

Table 4: Pearson Correlations for Metacomprehension Accuracy based on Predictions and Postdictions of Knowledge Assessment Performance Overall

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Declarative</td>
<td>--</td>
<td>.641</td>
<td>.935</td>
<td>.396</td>
<td>.383</td>
<td>.435</td>
<td>.560</td>
<td>.508</td>
</tr>
<tr>
<td>2. Integrative</td>
<td>--</td>
<td>.872</td>
<td>.407</td>
<td>.335</td>
<td>.542</td>
<td>.569</td>
<td>.578</td>
<td></td>
</tr>
<tr>
<td>3. Total</td>
<td>--</td>
<td>.441</td>
<td>.399</td>
<td>.528</td>
<td>.621</td>
<td>.592</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. MetaPre M1</td>
<td>--</td>
<td>.746</td>
<td>.498</td>
<td>.531</td>
<td>.616</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. MetaPre M2</td>
<td>--</td>
<td>.448</td>
<td>.440</td>
<td>.590</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. MetaPost All</td>
<td>--</td>
<td>.794</td>
<td>.781</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. MetaPost Declarative</td>
<td>--</td>
<td>.585</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>8. MetaPost Integrative</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. All correlations significant at the .01 level.
The correlation between predictions, postdictions and actual performance were also evaluated for each condition. Tables 5-8 represent Pearson correlations for the control, advanced organizer, feedback, and GCMD conditions on the five variables representing Knowledge Assessment Test performance (Declarative, Integrative, Total), predictions of performance following Module 1 (MetaPre M1) and Module 2 (MetaPre M2) of the tutorial, and postdictions of overall performance (MetaPost All), declarative (MetaPost Declarative), and integrative performance (MetaPost Integrative). When each condition was evaluated individually, the GCMD condition exhibited significant positive correlations for metacomprehension accuracy. This finding held true for both declarative knowledge and integrative knowledge. The feedback condition also had a significantly high correlation on integrative knowledge for Module 1.
Table 5: Pearson Correlations for Metacomprehension Accuracy based on Predictions and Postdictions of Knowledge Assessment Performance for Control Condition

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
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<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control (n = 17)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Declarative</td>
<td>--</td>
<td>.356</td>
<td>.910**</td>
<td>.157</td>
<td>.082</td>
<td>-.048</td>
<td>-.089</td>
<td>.061</td>
</tr>
<tr>
<td>2. Integrative</td>
<td>--</td>
<td>.711**</td>
<td>.149</td>
<td>.218</td>
<td>.444</td>
<td>.189</td>
<td>.593*</td>
<td></td>
</tr>
<tr>
<td>3. Total</td>
<td>--</td>
<td>.184</td>
<td>.159</td>
<td>.161</td>
<td>.017</td>
<td>.309</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. MetaPre M1</td>
<td>--</td>
<td>.786**</td>
<td>.570*</td>
<td>.350</td>
<td>.546*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. MetaPre M2</td>
<td>--</td>
<td>.383</td>
<td>.026</td>
<td>.610**</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>6. MetaPost All</td>
<td>--</td>
<td>.575*</td>
<td>.754**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. MetaPost Declarative</td>
<td>--</td>
<td>.147</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>8. MetaPost Integrative</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

*Note. *Correlation significant at the .05 level; **correlation significant at the .01 level.*
Table 6: Pearson Correlations for Metacomprehension Accuracy based on Predictions and Postdictions of Knowledge Assessment Performance for Advanced Organizer Condition

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Organizer (n = 17)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Declarative</td>
<td>--</td>
<td>.576*</td>
<td>.891**</td>
<td>.372</td>
<td>.412</td>
<td>.728**</td>
<td>.862**</td>
<td>.650**</td>
</tr>
<tr>
<td>2. Integrative</td>
<td>--</td>
<td>.855**</td>
<td>.238</td>
<td>.241</td>
<td>.658**</td>
<td>.689**</td>
<td>.480</td>
<td></td>
</tr>
<tr>
<td>3. Total</td>
<td>--</td>
<td>.344</td>
<td>.369</td>
<td>.781**</td>
<td>.875**</td>
<td>.639**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. MetaPre M1</td>
<td>--</td>
<td>.756**</td>
<td>.477</td>
<td>.541*</td>
<td>.576*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. MetaPre M2</td>
<td>--</td>
<td>.633**</td>
<td>.593*</td>
<td>.799**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. MetaPost All</td>
<td>--</td>
<td>.898**</td>
<td>.859**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. MetaPost Declarative</td>
<td>--</td>
<td>.771**</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>8. MetaPost Integrative</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

*Note.* *Correlation significant at the .05 level; **correlation significant at the .01 level.
Table 7: Pearson Correlations for Metacomprehension Accuracy based on Predictions and Postdictions of Knowledge Assessment Performance for Feedback Condition

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Feedback (n = 17)</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Declarative</td>
<td></td>
<td>--</td>
<td>.628**</td>
<td>.946**</td>
<td>.276</td>
<td>.326</td>
<td>.580*</td>
<td>.522*</td>
</tr>
<tr>
<td>2. Integrative</td>
<td></td>
<td>--</td>
<td>.847**</td>
<td>.537*</td>
<td>.430</td>
<td>.595*</td>
<td>.470</td>
<td>.632**</td>
</tr>
<tr>
<td>3. Total</td>
<td></td>
<td></td>
<td>--</td>
<td>.413</td>
<td>.402</td>
<td>.645**</td>
<td>.553*</td>
<td>.584*</td>
</tr>
<tr>
<td>4. MetaPre M1</td>
<td></td>
<td></td>
<td>--</td>
<td>.871**</td>
<td>.435</td>
<td>.519*</td>
<td>.634**</td>
<td></td>
</tr>
<tr>
<td>5. MetaPre M2</td>
<td></td>
<td></td>
<td></td>
<td>--</td>
<td>.363</td>
<td>.543*</td>
<td>.410</td>
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</tr>
<tr>
<td>6. MetaPost All</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>--</td>
<td>.895**</td>
<td>.787**</td>
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<td>7. MetaPost Declarative</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>--</td>
<td>.786**</td>
<td></td>
</tr>
<tr>
<td>8. MetaPost Integrative</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

*Note.* *Correlation significant at the .05 level; **correlation significant at the .01 level.
Table 8: Pearson Correlations for Metacomprehension Accuracy based on Predictions and Postdictions of Knowledge Assessment Performance for GCMD Condition

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<tbody>
<tr>
<td>GCMD (n = 17)</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>1. Declarative</td>
<td>--</td>
<td>.894**</td>
<td>.984**</td>
<td>.778**</td>
<td>.657**</td>
<td>.525*</td>
<td>.755**</td>
<td>.693**</td>
</tr>
<tr>
<td>2. Integrative</td>
<td>--</td>
<td>.960**</td>
<td>.783**</td>
<td>.586*</td>
<td>.531*</td>
<td>.725**</td>
<td>.679**</td>
<td></td>
</tr>
<tr>
<td>3. Total</td>
<td>--</td>
<td>.800**</td>
<td>.645**</td>
<td>.541*</td>
<td>.763**</td>
<td>.706**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. MetaPre M1</td>
<td>--</td>
<td>.751**</td>
<td>.529*</td>
<td>.700**</td>
<td>.767**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. MetaPre M2</td>
<td>--</td>
<td>.478</td>
<td>.571*</td>
<td>.575*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. MetaPost All</td>
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<td>.729**</td>
<td>.781**</td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>7. MetaPost Declarative</td>
<td>--</td>
<td>.561*</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>8. MetaPost Integrative</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note. *Correlation significant at the .05 level; **correlation significant at the .01 level.

Figure 3 depicts the Pearson correlations for metacomprehension accuracy based on prediction of knowledge assessment performance for Modules 1 and 2 across all conditions. For both Module 1 and 2, regarding integrative knowledge, metacomprehension accuracy was greatest for the GCMD condition, followed by the feedback condition, then the advanced organizer condition, and, lastly, the control condition. In terms of declarative knowledge, metacomprehension accuracy was highest again for the GCMD condition, but followed by the advanced organizer condition, then the feedback conditions, and, finally, the control condition.
By convention, in behavior sciences, correlation coefficients, regardless of sign, can be interpreted as .10 as small, .30 as medium, and .50 as large (Green & Salkind, 2005). To determine if there was a significant difference between condition correlations, each correlation coefficient was converted to a $z$-score through Fisher’s $r$-to-$z$ transformation (Cohen & Cohen, 1983). Table 9 lists the results of the analysis, based on total knowledge assessment performance. The GCMD condition demonstrated significantly higher metacomprehension accuracy than the remaining conditions for Module 1 (MetaPre M1). Indeed, the GCMD condition had the greatest significant difference as compared to the control condition primarily, followed by the advanced organizer condition, and then the feedback condition in Module 1. Similar trends were observed in for Module 2, but they did not hold to be significant. The feedback condition also showed a trend toward higher metacomprehension accuracy as compared to the
control condition, followed by the advanced organizer condition. Significant differences were not found in these instances, however.

Table 9: Fisher's $r$-to-$z$ Transformation of Metacomprehension Accuracy Based on Total Knowledge Assessment Performance

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Module 1 Survey</th>
<th>Module 2 Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1-tail $p$</td>
<td>2-tail $p$</td>
</tr>
<tr>
<td>Control – Adv Org</td>
<td>.324</td>
<td>.648</td>
</tr>
<tr>
<td>Control – Feedback</td>
<td>.252</td>
<td>.503</td>
</tr>
<tr>
<td>Control – GCMD</td>
<td>.008</td>
<td>.016</td>
</tr>
<tr>
<td>Adv Org – Feedback</td>
<td>.416</td>
<td>.831</td>
</tr>
<tr>
<td>Adv Org – GCMD</td>
<td>.025</td>
<td>.050</td>
</tr>
<tr>
<td>Feedback – GCMD</td>
<td>.041</td>
<td>.081</td>
</tr>
</tbody>
</table>

Regarding postdiction analysis, Figure 4 depicts the Pearson correlations for metacomprehension postdiction of knowledge assessment performance and actual performance across conditions. With the exception of the control group at $r(17) = .161, p = .537$, the remaining conditions, advanced organizer at $r(17) = .781, p < .001$, feedback at $r(17) = .645, p = .005$, and GCMD alone at $r(17) = .541, p = .025$, also showed significant positive correlations between total knowledge assessment score and overall post knowledge assessment metacomprehension (postdiction). In other words, learners in
these three conditions exhibited more accuracy in predicting their understanding of the tutorial material after the knowledge assessment test, than those in the control condition. To determine if there was a significant difference between condition correlations, each correlation coefficient was converted to a z-score through Fisher’s r-to-z transformation (Cohen & Cohen, 1983). These results are listed in Table 10. The outcomes indicated that the advanced organizer condition demonstrated significantly higher postdiction accuracy than the control condition. The feedback and GCMD conditions, although significant correlations, were not significantly different as compared to each other and the remaining conditions.

![Figure 4: Pearson Correlations for Metacomprehension Postdiction of Knowledge Assessment Performance and Actual Performance across Conditions](image-url)
Table 10: Fisher's r-to-z Transformation of Metacomprehension Postdiction Accuracy

<table>
<thead>
<tr>
<th>Conditions</th>
<th>1-tail p</th>
<th>2-tail p</th>
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</thead>
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<td>0.010</td>
<td>0.019</td>
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<td>Control – Feedback</td>
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<td>Control – GCMD</td>
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<tr>
<td>Adv Org – Feedback</td>
<td>0.228</td>
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</tr>
<tr>
<td>Adv Org – GCMD</td>
<td>0.121</td>
<td>0.242</td>
</tr>
<tr>
<td>Feedback – GCMD</td>
<td>0.335</td>
<td>0.670</td>
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**Self-Efficacy**

Scores on the 8-item Self-Efficacy Measure were based on a 10-point scale, with higher scores indicative of greater self-efficacy. After assessing whether self-efficacy was equally distributed across the four experimental conditions, scores were correlated with performance on the Knowledge Assessment Test, mental model accuracy, and the two interpretations of metacomprehension accuracy (i.e., based on level of understanding and based on predictions/postdictions of performance).
Equality of Self-Efficacy across Conditions

A one-way between groups ANOVA was conducted to ensure the four experimental conditions exhibited similar self-efficacy levels as would be expected with groups formed with random assignment. Results indicated the main effect of condition on mean self-efficacy scores was not significant, $F(3, 64) = 1.16, p = .331$. Participants in the control ($M = 5.65, SD = .67$), advanced organizer ($M = 5.15, SD = 1.12$), feedback ($M = 5.40, SD = .60$), and GCMD ($M = 5.49, SD = .73$) groups exhibited similar degrees of self-efficacy.

Self-Efficacy and Knowledge Assessment Performance

To evaluate the relationship between self-efficacy and knowledge assessment performance. Pearson correlations were conducted on mean self-efficacy scores and the percent correct for the Declarative, Integrative, and Total subsections of the Knowledge Assessment Test overall and then for each condition. Overall results indicated no significant correlations between self-efficacy and the three knowledge assessment measures, as shown in Table 11. Results for each condition are presented in Tables 12-15 and again revealed no significant correlations between self-efficacy and knowledge assessment performance. It is also noteworthy that, as shown in Table 15, self-efficacy was negatively correlated with performance on the Knowledge Assessment Test for the GCMD condition, although these correlations were not significant.
Table 11: Pearson Correlations between Self-Efficacy and Knowledge Assessment, Mental Model Accuracy, and Metacomprehension Accuracy Measures for all Conditions

<table>
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<td>.158</td>
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</table>

Note. *Correlation significant at the .05 level; **correlation significant at the .01 level.
Table 12: Pearson Correlations between Self-Efficacy and Knowledge Assessment, Mental Model Accuracy, and Metacomprehension Accuracy Measures for Control Condition

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*Note.* *Correlation significant at the .05 level; **correlation significant at the .01 level.
Table 13: Pearson Correlations between Self-Efficacy and Knowledge Assessment, Mental Model Accuracy, and Metacomprehension Accuracy Measures for Advanced Organizer Condition

<table>
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<td>.507*</td>
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Note: *Correlation significant at the .05 level; **correlation significant at the .01 level.
Table 14: Pearson Correlations between Self-Efficacy and Knowledge Assessment, Mental Model Accuracy, and Metacomprehension Accuracy Measures for Feedback Condition

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<td></td>
<td></td>
<td>.871**</td>
<td>.435</td>
<td>.519*</td>
<td>.634**</td>
</tr>
<tr>
<td>9. MetaPre M2</td>
<td></td>
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<td></td>
<td></td>
<td>.363</td>
<td>.543*</td>
<td>.410</td>
</tr>
<tr>
<td>10. MetaPost All</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td>.895**</td>
<td>.787**</td>
</tr>
<tr>
<td>11. MetaPost Declarative</td>
<td></td>
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<td></td>
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<td>.786**</td>
</tr>
<tr>
<td>12. MetaPost Integrative</td>
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*Note. *Correlation significant at the .05 level; **correlation significant at the .01 level.*

60
Table 15: Pearson Correlations between Self-Efficacy and Knowledge Assessment, Mental Model Accuracy, and Metacomprehension Accuracy Measures for GCMD Condition

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
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<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
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<tbody>
<tr>
<td>GCMD ( (n = 17) )</td>
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<tr>
<td>1. Self-Efficacy</td>
<td>--</td>
<td>-.202</td>
<td>-.002</td>
<td>-.127</td>
<td>.242</td>
<td>.046</td>
<td>-.085</td>
<td>.079</td>
<td>-.205</td>
<td>.284</td>
<td>-.014</td>
<td>.248</td>
</tr>
<tr>
<td>2. Declarative KA</td>
<td></td>
<td>--</td>
<td>.894**</td>
<td>.984**</td>
<td>.298</td>
<td>.687**</td>
<td>.336</td>
<td>.778**</td>
<td>.657**</td>
<td>.525*</td>
<td>.755**</td>
<td>.693**</td>
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<tr>
<td>3. Integrative KA</td>
<td></td>
<td></td>
<td>--</td>
<td>.960**</td>
<td>.321</td>
<td>.651**</td>
<td>.356</td>
<td>.783**</td>
<td>.586*</td>
<td>.531*</td>
<td>.725**</td>
<td>.679**</td>
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<tr>
<td>4. Total KA</td>
<td></td>
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<td></td>
<td>--</td>
<td>.315</td>
<td>.690**</td>
<td>.353</td>
<td>.800**</td>
<td>.645**</td>
<td>.541*</td>
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<td>5. Mental Model Accuracy</td>
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<td>.275</td>
<td>.078</td>
<td>-.119</td>
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<td>6. MetaKnowledge M1</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td>.496*</td>
<td>.655**</td>
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<td>7. MetaKnowledge M2</td>
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<td>.441</td>
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<td>8. MetaPre M1</td>
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<td>.751**</td>
<td>.529*</td>
<td>.700**</td>
<td>.767**</td>
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<td>9. MetaPre M2</td>
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<td></td>
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<td>.478</td>
<td>.571*</td>
<td>.575*</td>
</tr>
<tr>
<td>10. MetaPost All</td>
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<td>.729**</td>
<td>.781**</td>
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<tr>
<td>11. MetaPost Declarative</td>
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<td></td>
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<td></td>
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<td>.561*</td>
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<tr>
<td>12. MetaPost Integrative</td>
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</table>

*Note. *Correlation significant at the .05 level; **correlation significant at the .01 level.*
Self-Efficacy and Mental Model Accuracy

Pearson correlations were also used to evaluate the relationship between self-efficacy and the accuracy of participants’ mental models overall and for each condition. As shown in Table 11, the overall analysis showed the correlation between self-efficacy and MMA was not significant at the .05 level. Likewise, for each condition, there were no significant correlations between self-efficacy and the MMA measure, as illustrated in Tables 12-15.

Self-Efficacy and Metacomprehension Accuracy

Self-efficacy levels were correlated with measures associated with the two assessments of metacomprehension accuracy based on participants’ level of understanding, and predictions/postdictions of performance on the Knowledge Assessment Test overall and for each condition. Accordingly, this analysis correlated mean self-efficacy scores with the following variables: MetaKnowledge M1, MetaKnowledge M2, MetaPre M1, MetaPre M2, MetaPost All, MetaPost Declarative, and MetaPost Integrative.

Results overall, presented in Table 11, revealed self-efficacy was positively correlated with level of understanding for Module 1 (MetaKnowledge M1) and Module 2 (MetaKnowledge M2). Self-efficacy was also positively correlated with participants prediction of their performance on the Knowledge Assessment Test after Module 1 (MetaPre M1) and Module 2 (MetaPre M2), and their postdictions of performance overall
(MetaPost All), and on the declarative and integrative sections (MetaPost Declarative and MetaPost Integrative, respectively).

Correlations between these variables were also conducted for each condition. Results for the control condition indicated significant positive correlations between self-efficacy and MetaKnowledge M1, MetaKnowledge M2, and MetaPre M1 (see Table 12). For the advanced organizer condition, self-efficacy was positively correlated with all seven variables (MetaKnowledge M1, MetaKnowledge M2, MetaPre M1, MetaPre M2, MetaPost All, MetaPost Declarative, and MetaPost Integrative), as shown in Table 13. Similarly, results for the feedback condition indicated self-efficacy was positively correlated with five of the seven variables (MetaKnowledge M1, MetaKnowledge M2, MetaPre M1, MetaPre M2, and MetaPost Integrative), illustrated in Table 14. In contrast to these findings, none of the correlations between self-efficacy and the seven metacomprehension accuracy variables for the GCMD alone condition were significant, as shown in Table 15. Figure 5 summarizes these findings through Pearson correlation values for each condition (SE vs. DMC, SE vs. IMC).
Figure 5: Pearson Correlations for Self-Efficacy & Metacomprehension across Conditions

In summary, self-efficacy appears to have a more positive effect with metacomprehension accuracy for participants in the control, advanced organizer, and feedback conditions than those in the GCMD condition.
DISCUSSION

The findings of this study suggest that learners developing concept maps on their own led to improvements in metacomprehension accuracy, as assessed through self-reported level of understanding and prediction and postdiction of knowledge assessment performance. In addition, results support the theory that accurate mental model development facilitates learning. Specific findings across conditions and measures are discussed next.

Metacognitive Outcomes

Metacomprehension Accuracy

Evaluation of both measures of metacomprehension accuracy (i.e. levels of understanding and prediction) yielded significant results for the two concept mapping conditions, feedback and GCMD.

Metacomprehension Accuracy based on Level of Understanding

Findings showed a significant correlation of level of understanding with knowledge assessment performance overall for both modules of the tutorial.
Interestingly, both concept mapping conditions, feedback and GCMD, had significantly high correlations of level of understanding with integrative and total knowledge assessment performance for the declarative module (Module 1) of the tutorial. GCMD also showed a significantly high correlation pertaining to declarative knowledge assessment in the Module 1 (declarative knowledge). Although, the control group did show high correlations for declarative and total knowledge assessment, it did not have similar results for integrative knowledge assessment. In addition, unlike any other condition, the feedback condition had significantly high correlations of level of understanding with integrative and total knowledge assessment performance for the Module 2 (strategic knowledge) of the tutorial, perhaps indicating that feedback helped with level of understanding of strategic knowledge.

**Metacomprehension Accuracy based on Predictions and Postdictions of Knowledge Assessment Performance**

Significant results were also found in evaluating metacomprehension accuracy via learners’ assessment of their perceived likely performance and actual performance on the Knowledge Assessment Test. Correlations conducted for all conditions revealed positive correlations for both declarative and integrative knowledge. In contrast, when each condition was evaluated individually, the GCMD condition primarily exhibited significant positive correlations for metacomprehension accuracy. This finding held true for both declarative knowledge and integrative knowledge. The result suggests that the metacomprehension accuracy for the GCMD was better than that of the control, advanced
organizer, and feedback conditions. Specifically, for both Module 1 and 2, regarding integrative knowledge, metacomprehension accuracy was greatest for the GCMD condition, followed by the feedback condition, then the advanced organizer condition, and, lastly, the control condition. In terms of declarative knowledge, metacomprehension accuracy was highest again for the GCMD condition, but followed by the advanced organizer condition, then the feedback conditions, and, finally, the control condition.

Through data transformation, the metacomprehension accuracy correlations were evaluated for significant differences between conditions. Only the GCMD condition demonstrated significantly higher metacomprehension accuracy than the remaining conditions in regards to declarative module (Module 1) of the tutorial. Specifically, the GCMD condition was significantly higher in metacomprehension accuracy as compared to the control condition primarily, followed by the advanced organizer condition, and then the feedback condition. Although not significant, a similar trend was observed for strategic module (Module 2) of the tutorial. As is the case with any experiment, a larger sample size might have yielded different results. In addition, the findings for metacomprehension accuracy are further supported by the lack of a significant correlation between metacomprehension accuracy and self-efficacy in the GCMD condition. In other words, it supports that the significantly higher metacomprehension accuracy in the GCMD condition is not the result of self-efficacy, but likely that of the concept mapping intervention.

Also worth noting, with the exception of the control group, the remaining conditions also showed significant positive correlations between total knowledge assessment score and post knowledge assessment metacomprehension. In other words,
learners in these three conditions exhibited more accuracy in predicting their understanding of the tutorial material after the Knowledge Assessment Test, than those in the control condition, with the advanced organizer condition having significantly higher postdiction accuracy than the control condition.

Finally, it was hypothesized that the feedback condition would likely exhibit the highest metacomprehension accuracy. This prediction was based on the idea that the feedback provided would communicate to the learner how accurate their assumptions on conceptual relations were in developing their concept maps. In turn, they would be more likely to try to determine where knowledge gaps existed and correct them. However, with only one expert model behind the concept mapping task and likely several correct variations of the concept model, it may be that some feedback provided inadvertently confused learners. As such, there may have been a detrimental effect on their understanding of the training material itself and in their understanding of their knowledge base, or metacomprehension accuracy. For instance, in an early study, Trowbridge and Cason (1932) examined the impact of different forms of feedback on the learning process. They looked at the differences in providing no feedback, irrelevant feedback, qualitative feedback (right/wrong), and quantitative feedback (degree of correct). Their study showed that quantitative feedback yielded the best performance, qualitative feedback slightly improved performance, and irrelevant feedback actually hindered performance. The goal in the current study was to provide quantitative feedback to participants on the accuracy of their concept map as they progressed through the tutorial. However, being that there was only one expert map used as a comparison and possibly multiple correct variations to the concept map, the feedback to participants may have...
been inaccurate or irrelevant. Furthermore, a study by Katzeff (1990) emphasized the relationship between mental model development and feedback. The study showed that poor feedback leads to an incorrect mental model. In the current study, if the feedback provided was less than accurate, in other words not truly representative of the accuracy of the learners’ models, then it may have had a detrimental effect on their understanding of the material. For example, if some participants had created a concept map that was more correct than the percent correct feedback reported to him/her, it may have had an impact on their understanding of the material itself, their related mental model, and in the self-assessment of their knowledge base. In sum, these factors possibly compromised the intervention effects and negatively impacted results on metacomprehension accuracy, mental model development, and performance on the knowledge assessment test.

**Self-Efficacy and Metacomprehension Accuracy**

As stated earlier, all four conditions (control, advanced organizer, feedback, and GCMD) had similar self-reported self-efficacy levels amongst participants. Further evaluation of self-efficacy, revealed that in contrast to the other conditions, the GCMD condition alone showed that self-reported self-efficacy was not correlated with metacomprehension accuracy, as calculated by self-reported prediction of knowledge assessment performance. The findings suggests that higher metacomprehension accuracy observed in the GCMD condition was not the result of self-efficacy, but likely that of the study intervention. Specifically, since self-efficacy was not correlated with declarative or integrative metacomprehension for the GCMD condition, the results suggest self-efficacy
was not behind the higher level of metacomprehension accuracy exhibited by participants in the GCMD condition.

Cognitive Outcomes

Mental Model Accuracy

As stated previously, the mental model measure used in this study was card sorting, via the TPL-KATS card sort program. Analysis of mental model accuracy yielded no significant results, however some underlying causes may have interfered with how accurately these findings depicted the effect of the concept mapping intervention. First, based on observations of participants during the experiment, it appeared that some had difficulty with the TPL-KATS concept map software interface. This may have negatively impacted their performance on the task, perhaps interfering with accurate mental model development. Specifically, the software interface did not seem to allow learners to easily manipulate the concepts as they worked through the tutorial. In addition, many students complained of not being able to zoom-out and get a ‘big picture’ of their concept map. In turn, this may have depressed the effect of the concept mapping intervention on mental model development in the feedback and GCMD conditions. Although quantitative data was not collected that could support the role of the software as an extraneous variable, this possibility is worth considering in future research.
Secondly, it is possible the card sorting task did not adequately tap into the learner’s mental model. For example, a study examining convergence between three mental model assessments (pairwise relatedness ratings using Pathfinder, concept mapping, and card sorting) found that although card sorting and concept mapping had the highest correlation of all the comparisons, it was relatively small (Evans, Jentsch, Hitt, Bowers, & Salas, 2001). Conceivably, mental model development stemming from a concept mapping task may not be easily detectable through a card sorting task. At the same time, since concept mapping was used as the study intervention, it could not be used for mental model assessment without giving an advantage to the conditions involving concept maps.

Finally, the expert model of the concept map was based on a different subject matter expert (SME), then that of the card sorting data. This may have affected the mental model results for the advanced organizer and feedback conditions. The theory behind the feedback condition was that learners receiving percent correct feedback would use this information toward identifying and correcting existing knowledge gaps, thereby impacting their associated mental model. Likewise, participants in the advanced organizer condition would be able to validate their inferences against the concept map provided to them. In either case, if the expert models behind the concept map differed from that behind the card sort results, the information provided to the learners through feedback or an advanced organizer may have led to a different mental model of the training material than that measured by the card sorting task.
Knowledge Assessment

Evaluation of knowledge assessment outcomes between conditions did not yield significant findings. Although unclear as to the degree, two factors may have influenced the results. First, the declarative and integrative tests may not have been sensitive enough to accurately assess the effects of the study interventions, especially concerning a well-developed tutorial. The knowledge assessment test consisted of 25 questions in all; 15 on declarative knowledge and 10 on integrative knowledge. Although, no changes were expected in declarative knowledge between conditions, the declarative test scores averaged at 83% for the control group, an above average score. This may indicate that the test was not sensitive enough to detect differences between conditions. On the other hand, the integrative test scores for the control group averaged 74%, allowing reasonable room for improvement. However, this test involved only 10 questions and may not have adequately evaluated the differences in integrative knowledge.

Second, the limitations of the concept mapping task may have interfered with the intervention effect in the two concept mapping conditions. Yet, this is difficult to determine being that results in the advanced organizer condition also showed no improvement in knowledge assessment performance. However, for the purposes of future research, it is warranted to discuss the concept mapping task limitations specific to this study. For example, to minimize intrusion into the experimental process, the tutorial was only broken down into four sections, two for the declarative knowledge portion and two for the strategic knowledge portion. For participants of the concept mapping conditions (GCMD and feedback), the resulting concept lists used in the concept
mapping task had far more concepts in the first two sections covering declarative knowledge, compared to the last two sections covering strategic knowledge. As such, problems may have stemmed from this design that negatively impacted these learners’ understanding of the tutorial, as measured by mental model development and knowledge assessment. Specifically, it may be that learners were asked to integrate too many new concepts at once in the early sections. Possibly, the mental load asked of learners was too demanding. On the other hand, the disproportionate amount of declarative knowledge related concepts versus strategic knowledge concepts may have allowed learners to focus on the declarative knowledge far more than the strategic knowledge, partially explaining the differences between declarative and integrative knowledge assessment results. At the same time, integrative knowledge is a deeper level of knowledge than declarative, so it would be expected that related scores would be lower.

Nevertheless, other study outcomes support the use of concept maps in the learning process. For example, it was found that metacomprehension accuracy, based on prediction of knowledge assessment performance, in the GCMD condition was significantly higher than that of the other three conditions for declarative knowledge and both the GCMD and feedback conditions showed high correlations in metacomprehension via level of understanding. Research has shown that metacomprehension accuracy has a positive relationship with knowledge acquisition assessments (Fiore et al, 2002). As such, it is worth examining if a more elaborated list of integrative knowledge concepts, along with more sensitive knowledge assessment measures, would lead to improvements in learning in the GCMD or feedback conditions.
Relation between Mental Model Accuracy and Knowledge Assessment

Another significant finding of this study supports the need for learning tools that lead to accurate mental model development. Examination of the relationship between mental model accuracy and knowledge assessment showed that higher mental model accuracy, as measured by the correlation between the participant’s card sorting results and those of the subject matter expert, was positively related to higher knowledge assessment performance. This relationship supports that accurate mental model development is positively correlated to knowledge assessment. This held true for both the declarative and integrative portions and the knowledge assessment test as a whole. In summary, these findings support the vital role of accurate mental model development in the learning processes and suggest the need for training techniques focused on improving mental model development.

Concept Mapping

This primary intervention in this study was the concept mapping task as generated by the TPL-KATS software. The software was selected based on its ability to retrieve percent correct feedback, required for participants in the feedback condition. In hindsight, observation of participants during the experiment, along with examination of the results, suggests usability and software limitations of the TPL-KATS software may have confounded results, perhaps suppressing the effects of the concept mapping
intervention. In consideration of future research, several of these usability factors are worth discussing.

Specifically, because of software limitations surrounding loading in new concept lists for upcoming tutorial sections and concept map percent correct feedback, the tutorial was broken down into only four sections, as mention earlier. In attempting to separate the tutorial by logical stopping points in the content, the first two sections, covering declarative knowledge, had far more concepts than the last two sections, on strategic knowledge. This led to learners mapping the majority of the tutorial early in the concept mapping task. By the time participants received feedback, it may have become too taxing to incorporate many changes based on the feedback received, especially when the feedback did not give any indication to specifically where the error occurred.

Additional usability issues with the concept mapping software may have negatively affected participants in the two concept mapping conditions. For example, screen management and concept box size made it difficult to build, maneuver, and expand on the concept map. These usability factors may have interfered with participant’s ability to integrate knowledge effectively. Figure 5 depicts the concept mapping task after several concepts have been linked together.
Finally, many participants asked if there was a way to zoom-out so that they could see their concept map as a whole and keep sight of what they were doing. Plausibly, an inability to examine and easily build on the ‘big picture’ behind one’s concept map may have inhibited the contributions to learning from concept map development. In summary, a lack of the concept map ‘big picture’, difficulty in effectively responding to feedback provided, large variations in concept list length, and perhaps high mental workload in mapping several concepts at once may have interfered with mental model development and, thus, learning. Further examination of these factors will assist in determining the
degree, if any, to which they interfered with the effect of the concept mapping intervention on mental model development and possibly learning.
IMPLICATIONS FOR FUTURE RESEARCH

Individual Concept Mapping

As previously discussed, numerous factors likely contributed to the findings, and perhaps shielded the true effects of concept mapping in the learning process. Future research should consider the procedures and design of the concept mapping task. Specifically, it would be interesting to evaluate if the number of concepts given to learners at a time impacts motivation and self-explaining. In other words, it is worth examining if working memory limitations influence concept mapping. Perhaps participants asked to incorporate over 10 concepts at a time find it difficult to integrate all these new concepts at once. Additionally, asking participants to map a long list of concepts at once could lead to participants being more interested in completing the task itself, versus the learning process. The current study broke the tutorial into four sections, the first two were on declarative knowledge and contained a large number of concepts that had to be mapped. In contrast, the last two sections were on strategic knowledge and only offered a few concepts.

Consequently, several factors may have negatively impacted the concept mapping intervention as it relates to the strategic knowledge presented in the DDD tutorial. For instance, the strategic knowledge concepts were much fewer in number than in the declarative. As a result, learners may have placed less importance on strategic knowledge. In addition, the strategic knowledge concepts came at the end of the tutorial
where it may have been difficult to integrate them during the concept mapping task, both conceptually and in implementation due to the software usability issues. Expanding on the strategic knowledge concepts and incorporating them intermixed with declarative through the concept mapping processes may yield better results.

**Team Concept Mapping**

It is worth noting that concept map development may be useful in team settings. Coleman (1998) studied the impact on learning when students are prompted to explain their understanding of instructional material within a group in order to reach a consensus of their understanding of the topic. In that study, concept mapping was used as a mechanism to encourage collaborative explanation. Learners initially completed concept maps individually and then joined their groups to discuss and resolve discrepancies. Results showed that student participating in these group discussions developed more functional knowledge of the topic, were able to provide conceptually advanced explanations, and had higher levels of knowledge acquisition and retention. As such, further research should be conducted in using the GCMD technique or other concept mapping techniques with teams. It seems worthwhile to determine if team concept map building (i.e. team members building the concept map together while working through training material or a project) leads to productive communication between team members, shared mental model development, team cohesion, and increased team member
participation and commitment. Some individual factors may also improve, based on the team approach, such as improved individual metacomprehension and learning.
CONCLUSION

This study aimed at examining the influence of concept mapping to the learning processes. Specifically, mental model development, metacomprehension accuracy, and knowledge assessment were evaluated. Metacomprehension accuracy based on participant self-reported prediction of knowledge assessment performance was found to be significantly higher in the GCMD condition versus the control, advanced organizer, and feedback conditions. Likewise, both GCMD and feedback conditions showed significant correlations with knowledge assessment performance. However, no significant differences were found between conditions in mental model development and knowledge assessment. Yet, results support the relevance of accurate mental model development in knowledge assessment outcomes. In general, two opposing factors may have led to some insignificant findings. From one side, the experimental measures may not have been rigorous enough to filter out the effect from the concept mapping intervention itself. Conversely, software usability issues and the resulting limitations in experimental design worked negatively against the two concept mapping conditions. Future research in the GCMD approach will likely review cognitive workload related to the number of concepts being trained, concept mapping software usability, and the sensitivity of the measures involved.
APPENDIX A: STUDENT INFORMED CONSENT FORM
Introduction to Study:
This research, “Improving Metacomprehension and Learning through Graduated Concept Model Development,” is being conducted by principal investigator, Eleni D. Kring, a doctoral candidate of the Applied Experimental and Human Factors Psychology program.

In this research you will participate in a short training program designed to foster the development of knowledge associated with certain tasks. You will be presented with computer-based training materials that present information in multi-media format (e.g., text, audio, video) and you will be asked to learn this material as best you can. Your learning of this material will be assessed following review of the information presented. You are assured that your performance on these tasks will remain completely confidential (see below). Including training, performance, and paperwork, this experiment will last approximately 2 to 3 hours. Upon completion of the study course credit for participation in an experiment will be given in accordance with the procedures established within the Department of Psychology.

Risks and Benefits:
Participation in the current study does not involve any risks other than those commonly associated with the use of computer display terminals. Potential benefits include the development of guidelines for the appropriate use of training materials in a variety of differing task contexts. If you are injured during this study, as a result of the negligence of the Principal Investigator, the University of Central Florida, the Board of Regents of the State of Florida and the State of Florida shall be liable to the limited extent required by Florida law. You may seek appropriate compensation for injury by contacting the Personal Injury Insurance Coordinator at University of Central Florida Office of the General Counsel, Administration Building, Suite 350, Orlando, FL 32816-0015. The telephone number is (407) 823-2482. All inquiries to the Personal Injury Insurance Coordinator must be made in writing via either U.S. Mail, e-mail (gcounsel@mail.ucf.edu), or facsimile: (407) 823-6155."

Confidentiality of Personal Data:
All data you contribute to this study will be held in strict confidentiality by the researchers and will be kept under lock and key; that is, your individual data will not be revealed to anyone other than the researchers and their immediate assistants.

To insure confidentiality, the following steps will be taken: (a) only researchers will have access to the data in paper or electronic form. Data will be stored in locked facilities; (b) the actual forms will not contain names or other personal information. Instead, the forms will be matched to each participant by a number assigned by and only known to the experimenters; (c) only group means scores and standard deviations, but not individual scores, will be published or reported.
YOUR PARTICIPATION IN THIS RESEARCH IS COMPLETELY VOLUNTARY. YOU MAY WITHDRAW FROM PARTICIPATION AT ANY TIME WITHOUT PENALTY - THIS INCLUDES REMOVAL/DELETION OF ANY DATA YOU MAY HAVE CONTRIBUTED. SHOULD YOU DECIDE NOT TO COMPLETE THE TRAINING STUDY, HOWEVER, YOU WILL BE ELIGIBLE ONLY TO THE COURSE CREDIT FOR THAT PART OF THE STUDY YOU HAVE COMPLETED.

Consent and Signatures:
By signing this form I agree to participate in the study “Improving Metacomprehension and Learning through Graduated Concept Model Development,” conducted by principal investigators, Eleni D. Kring.

I have been given the opportunity to ask the research assistants any questions I may have. I have read the procedure described above. I voluntarily agree to participate in the procedure, and I have received a copy of this form. For any other questions regarding this research, I can contact: Eleni D. Kring, Psychology Department, University of Central Florida, Orlando, FL 32826. Phone: (321) 235-7683; E-mail: ekring@ideorlando.org

Signature: __________________________________________

Date: __________________________________________
APPENDIX B: BIOGRAPHICAL DATA FORM
Biographical Data Form

Please complete the following questions. Any information you provide is voluntary and will be kept strictly confidential. A participant number will be assigned to your responses and in no way will your name be associated with the data. The information you provide will be used only for the purposes of this study.

1. Age: ____
2. Gender: ____ M ____ F
3. SAT: _____ Verbal _____ Math
4. GPA: _____
5. Year in school: ____ Freshman ____ Sophomore ____ Junior ____ Senior
6. Major: ______________________
7. Native language (if not English): ________________
APPENDIX C: SELF-EFFICACY MEASURE
Self-Efficacy Measure

The following questions ask about your motivation for and attitudes about toward learning in general. Please circle the number that best describes the way you feel concerning that statement. **Remember there are no right or wrong answers, just answer as accurately as possible.**

1. I believe I will receive an excellent score on the tutorial knowledge assessments.

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2. I’m certain I can understand the most difficult material presented in the readings of the tutorial.

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3. I’m confident I can learn the basic concepts taught in the tutorial.

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4. I’m confident that I can understand the most complex material presented in the tutorial.

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5. I’m confident I can do an excellent job on the assignments and tests related to the tutorial.

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6. I expect to do well during my participation in the experiment.

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7. I’m certain I can master the skills being taught in the tutorial.

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8. Considering the difficulty of the tutorial content, I think I will do well during the experiment.

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88
APPENDIX D: DDD PREDICTION SURVEY
The following questionnaire is designed to inform us about the effectiveness of each module in the DDD Training Tutorial. Based on the module you just completed, please circle the number that best describes the way you feel concerning that question.

1) Overall, how helpful has this module been so far in teaching you about the DDD game?

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<tbody>
<tr>
<td>NOT AT ALL HELPFUL</td>
<td>SOMewhat HELPFUL</td>
<td>VERY HELPFUL</td>
<td></td>
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2) Overall, how easy or difficult have you found it to understand the concepts presented in this module?

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<tbody>
<tr>
<td>VERY DIFFICULT</td>
<td>FAIRLY EASY</td>
<td>VERY EASY</td>
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3) Overall, what is your level of understanding of the material presented in this module?

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<tr>
<td>VERY POOR</td>
<td>FAIRLY GOOD</td>
<td>VERY GOOD</td>
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4) Based on your level of understanding, how well would you do on multiple-choice questions that ask you about the material presented in this module?

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<td>None</td>
<td>Correct</td>
<td>Half Correct</td>
<td>All Correct</td>
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90
**Participant Number ______

**DDD Knowledge Assessment Questionnaire**

The following questionnaire is designed to inform us about how well the DDD Training Tutorial prepared you to respond to the knowledge assessment questions that you just completed. Please circle the number that best describes the way you feel concerning that question.

1) How well do you think you did **overall** on all the knowledge assessment questions that you just completed?

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2) How well do you think you did on the **Declarative Knowledge Assessment** questions that you just completed (that is, the first set of questions: the ones about the basic fundamentals in the DDD game such as scoring, identifying and attacking enemy targets, etc.)?

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3) How well do you think you did on the **Integrative Knowledge Assessment** questions that you just completed (that is, the second set of questions: the ones with animated pictures of different scenarios in the DDD game)?

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4) How well did the DDD Training Tutorial prepare you to answer all of these knowledge assessment questions (that is, both sets of questions)?

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<td><strong>Very Poorly</strong></td>
<td>VERY</td>
<td>FAIRLY</td>
<td>WELL</td>
<td>VERY</td>
<td>FAIRLY</td>
<td>WELL</td>
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5) **Overall**, how difficult was it to answer the knowledge assessment questions that you just completed?

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6) How difficult was it to answer the **Declarative Knowledge Assessment** questions that you just completed (that is, the first set of questions: the ones about the basic fundamentals in the DDD game such as scoring, identifying and attacking enemy targets, etc.)?

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<td>Easy</td>
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7) How difficult was it to answer the **Integrative Knowledge Assessment** questions that you just completed (that is, the second set of questions: the ones with animated pictures of different scenarios in the DDD game)?

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REFERENCES


