The purpose of this study was to gain an understanding of how undergraduate engineering students use constraint-based solid modeling (SM) software to successfully engage in computer-aided design (CAD) tasks charged to them in the context of an introductory engineering graphics course. Several designers, educators, and practitioners have suggested that CAD education needs reformation in order to better support learners’ application of SM software to the engineering design problems they encounter, and to adequately prepare them for the engineering workforce (Ault & Giolas, 2005; Branoff, Hartman, & Wiebe, 2003; Hamade & Artail, 2008; Ye, Peng, Chen, & Cai, 2004). It was these sentiments that provided impetus for the dissertation presented here—the central aspects of how SM is practiced and how SM instruction can be formulated and delivered are considered in the manuscripts of this study.

The first manuscript examines the application of a novel SM instructional regimen that employs worked examples in the form of tutorial videos. The study occurred over nine weeks in two sections of an introductory engineering graphics course that each met once a week. The cognitive load, performance, and the amount and type of transfer of learning experienced by the participants in the two experimental conditions (treatment and control) were used as determinants for the efficacy of the regimen. The results indicated that the treatment instruction was indeed more effective for reducing cognitive load and promoting transfer of learning, and there was a relationship that existed between the amount of germane
cognitive load experienced by participants and the amount of positive transfer that they achieved. These findings draw attention to the tacit relationship that underlies the aforementioned determinants in instructional contexts and it is evident that this synergy needs to be studied further.

The second manuscript proposed the Functional Interaction Model for Solid Modeling Processes (FIM) framework and explored how certain participants from the engineering graphics course practiced and dealt with design intent. The FIM framework was used to dissect the participants’ interactions with their solid models during the execution of CAD tasks on two separate occasions. This study not only introduced the FIM framework but it also used a Poisson regression with random and fixed factors as a means of statistically assessing the frequency data produced from an application of the FIM framework to the students’ performances. The results indicate that particular components of the FIM framework such as flow, locus, and complexity were more useful in characterizing the participants’ solid modeling interactions than other FIM framework components. This theoretical modeling and empirical validation approach to understanding design intent suggests that studying user interaction behaviors based on an underlying cognitive model deserves more consideration in the literature.
The Effects of Worked Examples on CAD Performance and Learning Efficiency

by
Spencer Barnes

A dissertation submitted to the Graduate Faculty of
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requirements for the Degree of
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Biography

Spencer Barnes grew up in Raleigh, NC and attended Enloe High School where he first gained exposure to the field of graphic design by taking courses in design, printmaking, photography, and visual communications. Upon graduation he attended North Carolina State University (NCSU) and there he attained a Bachelor of Graphic Design and a Master of Industrial Design. NCSU was also the institution where Spencer began his pursuit of a Doctorate of Education in Technology Education in the Department of Science, Technology, Engineering, and Mathematics Education.

During his graduate career, Spencer was able to engage in several opportunities to enhance his teaching repertoire. While pursuing his Master of Industrial Design degree he participated in the Certificate of Accomplishment in Teaching (COAT) Program sponsored by the NCSU Graduate School. The COAT program gave him a better understanding of how to deliver instruction to collegiate students and it allowed him to refine his skills as an instructor. Shortly after the program’s completion Spencer became an Adjunct Assistant Professor of Industrial Design in the NCSU College of Design where he specialized in surface modeling and car design. Near the middle of his doctoral studies he participated in another teaching program offered by the NCSU Graduate School, the Mentoring and Teaching Practicum (MATP). His mentor was Dr. Haywood Brown, the chair of the Department of Obstetrics & Gynecology at Duke University, and this is where Spencer gained exposure to the innovative types of instructional strategies employed at medical schools.
After spending more than a decade at NCSU, Spencer’s appreciation of the university’s mission and the opportunities that it has to offer has grown substantially. Outside of his studies and career, Spencer enjoys attending NCSU sporting events (e.g., football and basketball games). He is also engaged in fencing and plays tennis, and enjoys spending time with his family.
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First of all, I would like to thank my mother, father, sister, and other family members for their advice, support, and encouragement throughout the process of pursuing my doctoral degree. I would also like to express gratitude to all four members of my committee for their time and feedback on the comprehensive research project and journal articles presented within my dissertation. I would like to thank Dr. Eric Wiebe for his assistance and the direction that he provided for my dissertation, Dr. Jim Haynie for his thought provoking questions and candor, Dr. Ted Branoff for his technical guidance and for teaching me how to use solid modeling software effectively, and Bryan Laffitte for inspiring me to pursue graduate work in the fields of Industrial Design and Technology Education, and providing me with opportunities to teach.

I am also appreciative for all of the other people that made this experience very enjoyable and meaningful: Mrs. Cheryl Eatmon, who preached discipline and motivated me; Dr. Barbi Honeycutt, who taught me how to deliver quality instruction to my students; Dr. Kathleen Mapson and Dr. Tracie Addy, who provided me with camaraderie as they completed their doctoral studies; Mr. Walter Kelly, who assisted me with the administration of my study and made it a very “painless” process; Mr. Tih-Yuan Wang, who provided me with an abundance of technical advice; Dr. Jason A. Osborne, for helping me conjure an elaborate statistical technique to answer one of my research questions, and the late Dr. Doris Laryea from the NCSU Department of English, who always believed in me from the first day that I set foot on the NCSU campus.
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Introduction

The US Bureau of Labor Statistics (2010) projects that employment opportunities for engineers will increase by at least 11% within the next ten years. There are several reasons why this is likely to occur: a) engineers tend to engage in research endeavors and long-term projects, b) many senior engineers with years of experience are retiring, c) engineers generate the ideas that form the basis for product and process improvements, and d) the continued globalization of the engineering profession. Although the job demands of engineers are increasing in complexity and continue to expand, employers “expect their newly hired engineers or scientists to be able to ‘hit the ground running’”, thus students pursuing engineering degrees need more training in tools such as CAD to be competitive hires (Rodrigues, 2001, p. 181).

Several CAD educators and practitioners have suggested that CAD education needs reformation in order to better support learners’ application of SM software to engineering design problems and to adequately prepare them for entry into the engineering workforce. (Ahmed, 2007; Ault & Giolas, 2005; Hamade, 2009; Hamade & Artail, 2008; Branoff, Hartman, & Wiebe, 2003; Ye, Peng, Chen, & Cai, 2004). They have concluded that many graduates do not have the skills that are necessary for meeting the demands of the engineering and manufacturing industries. In order to meet those demands, students must have a comprehensive understanding of how to apply and manipulate design intent using SM design tools (Hartman, 2004). However, there have been few efforts presented within CAD literature that detail any exploration into how design intent is practiced and how it can be effectively and overtly integrated into a solid modeling instructional regimen.
The purpose of this dissertation was to present a foray into these issues and advance a comprehensive inquiry into how introductory SM instruction and practices could be enhanced. The following research questions were addressed by this study:

1. Do interactive videos for SM tasks that incorporate worked examples and instructional feedback alter participants’ instructional efficiency and learning efficiency?

2. Do interactive videos for SM tasks that incorporate worked examples and instructional feedback facilitate near and far transfer (i.e., the flexible translation and generalization of previously learned SM skills to novel SM tasks)?

3. Through this instructional regimen, do the participants’ mental models reflect an understanding of design intent?

To answer the research questions, two studies involving two sections of an introductory engineering graphics course were conducted during the Spring 2010 semester. The first study sought to investigate the efficacy of a novel SM instructional regimen and the second one attempted to explore how a student’s mental model of design intent might be revealed by how they practiced SM and interacted with geometric representations of mechanical parts. The students from each section of the course served as participants in the treatment and control conditions of the first study with a subset of them participating in the second study.

Two articles were produced from the data collected during the overall dissertation study. The first manuscript, *The Effects of Worked Examples on CAD Performance: An
*Exploratory Investigation*, describes how the first study was executed and presents its findings and implications. *The Application of a Functional Interaction Model for Solid Modeling Processes*, the second manuscript, proposes the Functional Interaction Model for Solid Modeling Processes (FIM) framework and how its application to the participants’ SM interactions can be statistically analyzed. Following the two manuscripts is a conclusion that synthesizes the findings from both manuscripts and describes future work. The appendix contains the dissertation prospectus.
The Effects of Worked Examples on CAD Performance: An Exploratory Investigation
Abstract

This study evaluated the efficacy of a novel instructional regimen for solid modeling instruction in the context of an introductory engineering graphics course. The performance of participants in a treatment condition utilizing the instructional regimen was compared to the performance of a control condition. Cognitive load and the type and amount of transfer were evaluated in conjunction with the participants’ performance on novel solid modeling tasks. A MANOVA and ad hoc aggregate measures of transfer and cognitive load suggest that the participants in the treatment condition experienced more positive transfer than those in the control condition and that the novel instructional regimen yielded more opportunities for the treatment participants to develop the cognitive skills needed to engage productively in learning solid modeling.
Introduction

The use of worked examples (WEs) has been gaining traction in a variety of disciplines (e.g., algebra, statistics, physics, etc.; Smith, Mestre, & Ross, 2010), and it is evident that the utilization of WEs in engineering education is effective. Several researchers have investigated how WEs influence the ways in which students learn complex engineering concepts and procedures. Reisslein, Atkinson, Seeling, and Reisslein (2006) observed how WEs employed in the context of electrical circuit analysis were able to enhance the learning of both intermediate as well as novice engineering students. Similarly, the research of Reisslein, Reisslein, and Seeling (2006) as well as Moreno, Reisslein, and Delgoda (2006), and Moreno, Reisslein, and Ozogul (2009) all indicated that WEs corresponding to the levels of proficiency that learners are attempting to attain were effective in promoting superior performance on engineering tasks. Although each of the preceding articles investigated WEs in the context of engineering education, none of them explicitly considered how CAD instruction, in particular solid modeling (SM) instruction, could benefit from the inclusion of WEs.

Clark and Mayer (2008) noted that e-Learning can be used to format WEs, making them interactive and potentially leading to greater learning gains. A few studies have been conducted that address how WEs, in the form of multimedia or e-Learning tutorials, could be used as a component of CAD instruction. Folkestad and de Miranda (2001) used screen recorded videos demonstrating how to complete CAD drawing exercises from beginning to end whereas Connolly and Maicher (2005) developed a web-based tutorial program that provided users with interactive feedback as they completed multi-view CAD drawings.
Branoff and Wiebe (2009) elaborated upon the use of tutorial videos as WEs in online learning for CAD instruction by integrating them into hybrid (i.e., blended learning) sections of an engineering graphics course that taught solid modeling. Here, some of the course instruction was presented face-to-face while the remaining content was delivered in a web-based format via an online learning management system. They assessed whether any learning gains occurred in the hybrid sections compared to sections of the same engineering graphics course taught in a traditional (face-to-face) manner. They recommended the application of hybrid learning for CAD instruction due to the flexibility of hybrid arrangements and the fact that student engagement is given consideration because instructional materials (e.g., tutorial videos) can be designed to encourage good study habits.

While all of the aforementioned studies have examined the application and delivery of WEs relative to CAD education, these explorations—however substantive in nature—possess a deficiency: no clear instructional strategy or regimen has been designed to address the incorporation of WEs into CAD education or solid modeling instruction. These inquiries offer little to no insight into the application or evaluation of the efficacy of such an instructional regimen. In response to these concerns, the current study proposes a novel adaptation of the *Four-Component Instructional Design* (4C/ID) model developed by van Merriënboer (1997) where WEs in the form of tutorial videos for solid modeling tasks are integrated into sections of an introductory engineering graphics course curriculum. Also, the authors suggest other pertinent factors that need to be considered and measured so that the efficacy of this instructional regimen can be accurately assessed. These include the amount of
cognitive effort imposed by the regimen and the type and amount of transfer that the regimen facilitates.

**Worked example-based learning and the 4C/ID Model**

A worked example or WE is a prototype or model of expert problem solving processes that provides learners with instructional support (i.e., scaffolding) during the completion of a task by serving as a hard scaffold or a “computer or paper-based cognitive tool” that directs learners’ attention relative to instructional content and guides their interactions with that content (Belland, Glazewski, & Richardson, 2008, p. 407). WEs typically consist of a problem formulation (e.g., givens), solution steps and strategies, and a final solution to the problem formulation (Renkl & Atkinson, 2010) and they can be designed in either a process-oriented format or a product-oriented format. Process-oriented WEs (process WEs) provide solution procedures and strategies as opposed to the final solution itself, while product-oriented WEs (product WEs) provide equal attention to the givens, goal states and relevant relationships between those states, and the final solution (van Gog, Paas, & van Merriënboer, 2006). The underlying strength of a WE lies in its ability to facilitate the acquisition, abstraction, and automation of schemata related to the structure and solution procedure(s) of a problem, and the broader categories of problems of which the problem under consideration is a part (Cooper & Sweller, 1987; Sweller & Cooper, 1985). Schemata are cognitive structures that organize and represent knowledge so that an individual is capable of directing the application of previously acquired knowledge toward the execution of a skill (Marshall, 1995). In the context of performing solid modeling tasks it is very likely that cognitive skills are necessary because of the nature of the tasks and the specialized
knowledge required to complete them (i.e., knowledge of the modeling process and the solid modeling software package; Wiebe, 2003).

According to VanLehn (1996) a cognitive skill is a skill that is applied to intellectual, “knowledge-intensive” (p. 514), and rich learning tasks such as problem solving in a specific domain or realm of subject matter. Cognitive skills take domain-specific knowledge and translate this information into responses and behaviors that manifest themselves during the execution of tasks within the domain and this translation process occurs because of the acquisition of schemata (Colley & Beech, 1989). The schemata contained within a cognitive skill are built from domain knowledge and principles, and get further developed as an individual executes tasks within that domain (Renkl & Atkinson, 2007). The 4C/ID model is an instructional design framework that addresses the usage and structuring of WEs for the attainment and application of cognitive skills. The premise behind the 4C/ID model is that the design of instructional regimens can be structured in a way that helps trainees engage in learning that requires the integration and coordination of cognitive skills in order to execute complex tasks and reach competency. The 4C/ID model does so by partitioning instruction into four components: whole-task practice, part-task practice, supportive information, and just-in-time information (van Merriënboer, 1997; van Merriënboer, Clark, & de Croock, 2002; van Merriënboer, Jelsma, & Paas, 1992). Whole-task practice occurs within task classes where each task class contains several learning tasks arranged in increasing complexity. It includes supportive information in the form of worked examples that present demonstrations and guidance intended to help the learners get acclimated to the task; as whole-task practice proceeds, the assistance (i.e., supportive information) provided to the
learner gradually fades so that the learner can perform the entire cognitive skill without any guidance. Part-task practice is separate from whole-task practice and focuses on developing the automaticity (e.g., speed and accuracy) of a cognitive skill and task performance. The just-in-time (JIT) information comes in the form of rules, step-by-step directions, and feedback for the execution of the cognitive skill and can be presented during whole-task practice and part-task practice. When the 4C/ID is applied to training, whole-task practice (in the context of a task class) occurs first and then part-task practice occurs subsequently. The whole-task practice includes supportive information and JIT information, and the part-task practice only includes JIT information. This workflow proceeds until all of the learning tasks in the task class are completed and the cognitive skill(s) are acquired (van Merriënboer, 1997).

**Efficiency**

Any task requiring the application of a cognitive skill has the potential to impose cognitive load, the psychological experience resulting from task complexity that surrounds and is imposed upon individuals during learning and performance. It is the psychological experience that arises from engaging in a task, and dependent on both individual differences and the complexity of the task (Moreno, 2010). Three types of cognitive load exist: intrinsic cognitive load (ICL), extraneous cognitive load (ECL), and germane cognitive load (GCL). ICL is caused by the amount and nature of the information that needs to be held in working memory (WM) during learning and performance (Schnotz & Kürschner, 2007). During learning, several elements of information (e.g., bits or chunks) pertaining to the content under consideration have to be held and maintained in WM. Depending their nature (i.e., whether
they are independent or dependent upon each other to be understood) WM capacity can be consumed in processing these elements and consequently depleted. This phenomena is called element interactivity, it can vary between two extremes (low and high), and interacts with an individual’s prior knowledge. Low element interactivity occurs when only a few elements need to be held in WM and these elements are processed in succession whereas high interactivity occurs when elements make reference to each other and “several elements must be manipulated in working memory simultaneously” (Sweller, van Merriënboer, & Paas, 1998, p. 260). Regarding element interactivity, prior knowledge allows the elements to be organized in ways such that WM functions efficiently because similar elements are aggregated into chunks (i.e., schemata) and are treated as one element, which frees WM capacity and reduces ICL. According to Moreno and Park (2010), the only other way to reduce ICL is to reduce the number of interactive elements that have to be maintained in WM—accomplished by segmenting and sequencing content so that learners do not have to assimilate all of the content at one time. When the design of instructional materials induces unnecessary element interactivity—irrelevant to the subject matter but related to how the content is presented—ECL arises (Paas, Renkl, & Sweller, 2003). For example, placing irrelevant or superfluous graphics and sounds within a multimedia tutorial on algebraic equations can lead to increased levels of ECL because none of these embellishments concern the content being presented and they inadvertently direct learners’ attention away from the focus of the presentation. Aside from misdirecting learners’ attention, the learners would then have to maintain and process the superfluous elements as well as the pertinent elements of the presentation in WM, increasing element interactivity and therefore depleting WM
capacity. Many times this type of cognitive load adversely affects learning because ECL is being imposed simultaneously with ICL, leaving little WM remaining to dedicate toward learning since the capacity of WM is fixed and cannot be exceeded (Mayer & Moreno, 2010). In scenarios where WM is not exhausted by the other forms of cognitive load, GCL can be induced. GCL is cognitive load that is solely associated with learning, that is, cognitive load imposed by the formation of schemata. Kalyuga (2010) suggested that “the sources of germane cognitive load are auxiliary cognitive activities designed to enhance learning outcomes or increase levels of learner motivation” (p. 53). Knowledge elaboration, the process of using prior knowledge to expand and refine new information on a perpetual basis and assimilate it with information contained in long-term memory, underlies the construction and automation of schemata (Kalyuga, 2009) which, in turn, actuates GCL. Once schemata have been constructed, their likelihood of usage can be strengthened and automated by constantly engaging in tasks that require their utilization. After a schema is automated it no longer causes GCL because it is does not require conscious maintenance and processing in WM. A synergy exists within the trilateral relationship between ICL, ECL, and GCL—free WM capacity can be dedicated to any of the three types of cognitive load and both ICL and ECL can actuate GCL, although ICL is a greater determinant for GCL. Sweller (2010) was well aware of this insight and expressed an intuitive understanding of this relationship by recommending that instructional design should attempt to impose ICL, if any cognitive load at all, because the element interactivity that causes ICL can be reduced by the processes of schema acquisition, construction, and automation (i.e., WM is used to form
connections between the interacting elements and to aggregate them into schemata and then automate the schemata) which are the fundamental sources of GCL.

Cognitive load measures are often supplemented by circumstantial data (e.g., test scores, number of errors, latency) from the context in which instruction and performance take place. This is because “a meaningful interpretation of a certain level of cognitive load can only be given in the context of its associated performance level and vice versa”, and when cognitive load is combined with other variables associated with learning, instructional conditions can be compared and the type of cognitive load imposed during different parts of the entire learning process can be ascertained (Paas, Tuovinen, Tabbers, & van Gerven, 2003, p. 67). Two means of aggregating cognitive load with other performance variables take the form of simple yet elegant statistical transformations called efficiencies. Efficiencies are capable of indicating the type and amount of cognitive load (e.g., ECL and GCL) imposed by a learning condition. The formulae for efficiencies utilize standardized performance scores and cognitive load scores. Instructional efficiency evaluates the relationship between the cognitive load that individuals experience while engaged in testing or assessments within a learning condition, and the amount of performance that they are able to achieve on those assessments. In comparison, learning efficiency considers the cognitive load that becomes present during training (e.g., reading a passage or watching a tutorial video) and learners’ test or assessment performance (Paas & van Merriënboer, 1993; Tuovinen & Paas, 2004). Each kind of efficiency can vary between two extremes—high efficiency and low efficiency—where high efficiency occurs when performance is maximized and a small amount of cognitive load is incurred, and low efficiency occurs when performance is low and the
amount of cognitive load incurred is high. The baseline for both kinds of efficiencies is an efficiency of zero \( E=0 \) where performance is equal to cognitive load. Instructional efficiency is indicative of the effects of GCL on learners because it stands to reason that if a learner has acquired, assimilated, and automated more schemata (i.e., gained more knowledge due to effective instruction) during learning, prior to taking a test, they will experience a smaller amount of cognitive load during testing, in contrast to learners who were not able to construct and elaborate upon schemata (i.e., gained less knowledge as a result of inadequate instruction) before taking the test (Paas & van Gog, 2006). Learning efficiency, on the other hand, is indicative of the ECL caused by instructional designs (van Gog & Paas, 2008). If an instructional condition has been designed to appropriately promote learning and deliver instruction then learners should experience a low amount of cognitive load during learning and should therefore have high test performance. If instruction has been designed inadequately, then learners will incur a high amount of cognitive load during learning and have low test performance. Accordingly, high learning efficiency implies that a certain instructional design is more effective than another because it imposes less ECL than an instructional design having low learning efficiency.

Transfer of Learning

Transfer of learning (transfer) concerns “how previous learning influences current and future learning, and how past or current learning is applied to similar or novel situations” (Haskell, 2001, p. 23) i.e., transfer is indicative of how well one is able to abstract, generalize, and apply the domain knowledge and skills that they have learned during training to their subsequent performance on problems or tasks that have varying degrees of
correspondence (i.e., similarity or difference) to the training task (Sternberg, 2009). The correspondence between two tasks primarily depends on two factors, the surface features and the deep structures of the tasks, and how learners represent these factors (Sloutsky & Yarlas, 2000; Yarlas & Sloutsky, 2000). A task’s surface features include the way(s) in which the task is presented to learners (e.g., cover story and context) and its deep structure pertains to the organization of the task and the procedures necessary to successfully complete it. The more that a learner accumulates experience with a task during training, the more likely it is that they will critically examine the task’s deep structure and look past the task’s surface features and perform better on transfer tasks. With regard to the correspondence between training tasks and transfer tasks, two types of transfer exist: near transfer and far transfer. Near transfer occurs when knowledge acquired from one task is applied to a new task containing a deep structure and surface features similar to the original task, whereas far transfer refers to the application of previous knowledge to a new task that is markedly different (e.g., different deep structure) from the training task (Gray & Orasanu, 1987).

Transfer also pertains to how beneficial or detrimental training can be to one’s ability to generalize and apply what has been learned during training. According to Kimball and Holyoak (2000) “transfer may be either positive or negative, depending on whether performance of the training task benefits or hinders performance of the transfer task” (p. 110). This simply means that positive transfer occurs when training facilitates superior performance on a near transfer or far transfer task whereas negative transfer happens when “participants actually perform worse on the transfer task than they would have if they had not been exposed to the initial training task in the first place” (Barnett & Ceci, 2002, p. 617).
Although rarely applied in studies assessing transfer, Gagné, Foster, and Crowley (1948) proposed several formulae that measure the magnitude of positive and negative transfer that gets instantiated as a result of an instructional regimen. These formulae, which were designed for experimental and learning contexts, take into account the percentage of positive or negative transfer occurring by comparing the performance of treatment and control conditions on the same near transfer or far transfer task, thereby “giving direct expression to [the] amount and direction of transfer” (p. 102). In particular, formula no. 5 quantifies the amount of transfer that an experiment’s treatment condition experiences when exposed to an instructional regimen provided that the treatment condition’s performance is compared to the performance of a control condition that did not receive the instructional regimen (Gagné, Foster, & Crowley, 1948, p. 103).

Summary

What has become evident from this consideration of the areas of worked example-based learning, cognitive load, and transfer is that they are all bound by a tacit relationship that becomes more explicit when their application to an instructional regimen is orchestrated by the 4C/ID model. WEs are able to alleviate ICL and ECL, and promote GCL during learning because they eliminate the need for one to hold or maintain all of the components of a task in WM (e.g., problem states, goal states, and the respective differences between these states). WEs focus an individual’s attention on the relevant aspects of a task and associated procedures such that the ICL imposed by the task is minimized and GCL maximized while acquiring relevant domain knowledge (Paas & van Gog, 2006; van Merriënboer, Kester, & Paas, 2006). Paas and van Merriënboer (1994) found that near transfer and far transfer are
enabled by WEs especially when WEs with varying surface features and deep structures are presented to learners during instruction. Both the whole-task practice and part-task practice are components of the 4C/ID model in which WEs can be integrated in order to increase cognitive skill acquisition and if properly utilized over the course of learning they can reduce cognitive load and promote effective transfer (Lim, Reiser, & Olina, 2009).

Purpose and Research Questions

This study sought to investigate how WEs, in the form of tutorial videos demonstrating solid modeling processes, could be structured according to an adaptation of the 4C/ID model. This design approach should facilitate increased performance and transfer exhibited by undergraduate engineering students on solid modeling tasks, along with an observed reduction in their associated cognitive load. The 4C/ID model adaptation enacted in this study was based upon practical considerations relative to the ways in which instruction was delivered to the participants via a course website. Two experimental conditions, a treatment condition and a control condition, were incorporated into the study – the treatment condition engaged in both whole-task practice and part-task practice of solid modeling tasks whereas the control condition only engaged in whole-task practice of the solid modeling tasks. The following research questions attempt to determine the efficacy of the instructional regimen and guide the authors’ investigation:

1. What is the effect of the adapted 4C/ID instructional regimen for solid modeling instruction on the performance and transfer (near and far) exhibited by the participants?
2. How is the amount of and type of cognitive load imposed upon participants affected during their engagement with the adapted 4C/ID instructional regimen?

Methods

Participants. The sampling frame consisted of 105 undergraduate students enrolled in two sections of an introductory engineering graphics course at a large Southeastern university. The students represented the following majors: aerospace engineering, civil engineering, mechanical engineering, landscape architecture, technology education, and textile engineering. The average age of the participants was 20 (SD = 3.33) with freshmen, sophomores, juniors, and seniors engaging in the study. Over 85% of the sample was male. Due to attrition the number of participants that fully completed the study differed from those originally included in the sampling frame – the treatment condition had n=13 and the control condition had n=8.

Materials. A questionnaire designed by one of the researchers was used to collect demographic information (e.g., age, gender, university classification, and major) about the participants. Three types of tutorial videos were produced for the experimental condition and the control condition of this study: videos that fully demonstrated WEs of SM activities (full videos), videos that partially demonstrated WEs of SM activities (partial videos), and videos that fully focused on design intent (design intent videos). Full videos served as a means of whole-task practice because learners engaged in the process of creating a solid model from beginning to end by following along with the video demonstration and it was during this process that they learned how to problem solve in the context of constraint-based solid
modeling software. Partial videos focused on refining the participants’ procedural skills for SM tasks e.g., a task may have involved multiple extrusions and it is necessary that the process of creating an extrusion becomes intuitive to the learners. Design intent videos emphasized design intent by presenting and demonstrating brief SM activities that reinforced the process of embedding intelligence and functionality into a model. These videos presented ways in which the application of design intent could be conceptualized (e.g., one of the videos demonstrated how to aggregate sketch elements in order make multiple ribs as one feature). The full videos were intended to assist the participants with learning the SM process, the partial videos provided participants with the opportunity to automatize aspects of their SM process, and the design intent videos offered a means of abstracting the skills learned in the full videos and partial videos so that they could be executed with accuracy, precision, and efficiency.

There were five SM lessons in the study and each lesson was accompanied by two SM exercises, a near transfer SM exercise and a far transfer SM exercise, that the participants had to complete at the end of the lesson. Lesson 1 covered basic sketching and the creation of simple base features (e.g., geometry), Lessons 2 and 3 discussed the creation of multiple orthographic sketches and their corresponding base and secondary features, Lesson 4 introduced the participants to ribs as structural elements as well as draft, and Lesson 5 presented circular and linear sketch patterns and feature patterns. The near transfer SM exercises had surface features and deep structures similar to the tasks presented in the videos (e.g., the revolve tool would be applicable to the video task and the near transfer SM exercise) whereas the far transfer SM exercises shared no surface features or deep structures
with the video tasks. All of the near transfer SM exercises and far transfer SM exercises were
scored as a proportion of 100 total points per exercise. *Lesson overviews* preceded each
tutorial video and SM exercise, displaying a picture of the goal state of the SM exercises (i.e.,
what the finished model was supposed to look like), indicating the units that the SM exercise
needed to be constructed in (e.g., inches or millimeters), and presenting the objectives that
the tutorial video was attempting to accomplish. The lesson overviews that were solely
associated with near transfer SM exercises and far transfer SM exercises presented a
schematic of each exercise and its associated metric.

Paas’ (1992) unidimensional 9-point Cognitive Load scale (referred to as *9-point CL Scale* from here on) was used to measure the cognitive load imposed on participants by the
tutorial videos and the SM exercises. The 9-point CL Scale is symmetrical and adaptable, and
asked participants about the amount of perceived mental effort they have experienced while
completing a task. According to van Gog and Paas (2008, p. 18) this instrument has
maintained a Cronbach’s Alpha ranging between .82 and .90 over the course of several
cognitive load studies. It is an unobtrusive instrument in the sense that it requires a minimal
amount of time to complete and does not have the propensity to disrupt participants’
engagement in tasks. The 9-pt CL Scale can be employed in an online or offline manner
meaning that it can assess the cognitive load that one is experiencing during the execution of
a task in real-time or it can measure cognitive load immediately after the task is completed.
The instrument presented the following question to participants: “How much mental effort
did you experience while completing the SM activity?” The nine response choices ranged
from “very, very low mental effort” (1) to “very, very high mental effort” (9) with “Neither
low nor high mental effort” (5) serving as the instrument’s baseline at the center of the scale. As participants’ responses on the 9-point CL Scale were utilized in determining the amount of instructional efficiency and learning efficiency that they experienced, the responses were coded from 1 to 9 during analysis.

Apparatus. All of the study’s materials were delivered via course websites (one for the treatment condition and one for the control condition) that were housed on the university’s learning management system and the participants gained access to all of the aforementioned materials via the websites. The course websites arranged each of the lessons associated with the study in a hierarchical manner where all of the materials associated with a particular lesson were grouped together. All of the tutorial videos (e.g., full videos, part videos, and design intent videos) were produced using Dassault SolidWorks™ as the SM software and Techsmith Camtasia™ as the screen capture recorder. The lesson overviews were made using Microsoft PowerPoint and Adobe Presenter. All of the data submitted from the demographic information questionnaire and the 9-pt CL Scales was collected through Acrobat.com.

Study Design and Procedure

The study spanned five lessons of an introductory engineering graphics course and used a quasi-experimental design with participants nested within two sections of the course. The two sections of the course that participated in the study were randomly assigned to each of the experimental conditions, treatment and control. A 2 X 5 mixed design was implemented with a between subjects factor of experimental condition with two levels (treatment and control) and within subjects repeated factor of lesson. See Table 1 for a schematic of the experimental design employed. The primary dependent variables of this
investigation were: near transfer SM score, far transfer SM score, and cognitive load – learning efficiency, instructional efficiency, and amount of positive or negative transfer (amount of transfer) all served as ad hoc outcome measures as they all required the primary dependent variables in their calculations.

Table 1. The experimental design utilized by the study. Participants’ engagement with the adapted 4C/ID instructional regimen during each lesson constituted an application of the treatment (X) and each observation (O_i) represents the participants’ completion of the near transfer SM exercises and the far transfer SM exercises associated with each lesson.

<table>
<thead>
<tr>
<th>Experimental Design</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
</tr>
<tr>
<td>Control</td>
</tr>
</tbody>
</table>

The study’s duration was five weeks with one lesson covered per week. The sections of the engineering graphics course in which the participants were enrolled met once a week. One week prior to the study, the researchers administered the questionnaire in order to collect demographic information about the participants and the study began the following week.

Treatment Condition: The instructional regimen for the treatment condition consisted of lesson overviews, one full video, one partial video, and one design intent video per lesson as well as one near transfer SM exercise and one far transfer SM exercise that had to be completed per lesson. At every class meeting the participants were introduced to the lesson overview and videos, and they had one week to view the videos and complete the SM transfer exercises associated with the lesson. The participants were instructed to view each video and immediately afterwards complete and submit a 9-pt CL Scale, indicating the amount of cognitive load that they experienced while viewing the video and attempting to follow along with the demonstration. The participants then completed the lesson’s near
transfer SM exercise and far transfer SM exercise and a 9-pt CL Scale for each exercise, respectively. This workflow proceeded until the end of the study.¹

Control Condition: The participants in this condition followed the exact same procedure as the participants in the treatment condition except the only videos viewed with each lesson were the same full videos viewed by the treatment participants. The control participants also submitted 9-pt CL Scales corresponding to the cognitive load that they experienced while viewing the full videos and completing the near transfer SM exercises and far transfer SM exercises, respectively.

Results

The statistical tests conducted utilized a significance criterion of .05 unless otherwise noted with Bonferroni corrections administered as post hoc procedures for all multivariate tests. Table 2 displays the treatment and control participants’ scores on each lesson’s near transfer SM exercise and far transfer SM exercise, along with the amount of cognitive load that they experienced during their completion of the exercises. Figures 2 and 3 display the amount of cognitive load that was imposed upon participants as they viewed the full videos, the partial videos, and the design intent videos.

Research Question 1: What is the effect of the adapted 4C/ID instructional regimen for solid modeling instruction on the performance and transfer (near and far) exhibited by the participants? A 2 X 5 mixed MANOVA was conducted with experimental condition as the between subjects factor, lesson as the within subjects factor, and the near transfer SM exercise and far transfer SM exercises no partial video or design intent video was included in the lesson.

¹ Due to the novelty of the subject matter addressed by the Lesson 4, full videos and near and far transfer SM exercises no partial video or design intent video was included in the lesson.
exercise scores and far transfer SM exercise scores from each lesson as dependent measures. Pillai’s Trace ($V$) was used as the multivariate coefficient for the MANOVA. Also, the amount of positive and negative transfer facilitated for each transfer SM exercise was considered using transfer formula no. 5 (see Figure 1). Although there was not a significant interaction between experimental condition and lesson, the MANOVA did reveal that a significant multivariate main effect for experimental condition existed with $V=.386$, $F(2, 18)=5.655$, $p=.012$, partial $\eta^2=.386$. Follow-up univariate ANOVAs revealed the treatment condition and control condition significantly differed on the near transfer SM exercises $F(1, 19)=11.739$, $p=.003$, partial $\eta^2=.382$ with the treatment condition generally scoring higher on the exercises than the control condition. Further post-hoc analyses indicated that these significant differences between the groups on the near transfer SM exercises occurred on the Lesson 4 near transfer SM exercise and Lesson 5 near transfer SM exercise, where participants in the treatment condition achieved higher scores on the exercises than participants in the control condition. As can be seen in Table 3 it is evident that the instructional regimen (i.e., treatment) facilitated varying amounts of positive transfer in the majority of the near transfer SM exercises and far transfer exercises with the Lesson 4 near transfer and far transfer SM exercises and the Lesson 5 near transfer exercise having higher levels of positive transfer than the other exercises. The only exception lies with the Lesson 1 far transfer SM exercise which exhibited a negligible amount of negative transfer due to the instructional regimen.
Table 2. The mean scores and corresponding standard deviations for all of the performance scores and cognitive load scores for all of the near transfer SM exercises and far transfer SM exercises.

<table>
<thead>
<tr>
<th>Lesson</th>
<th>Near Transfer SM Ex. Score</th>
<th>Near Transfer SM Ex. CL</th>
<th>Far Transfer SM Ex. Score</th>
<th>Far Transfer SM Exercise CL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>1</td>
<td>.76</td>
<td>.16</td>
<td>4.57</td>
<td>1.54</td>
</tr>
<tr>
<td>2</td>
<td>.81</td>
<td>.22</td>
<td>4.68</td>
<td>1.64</td>
</tr>
<tr>
<td>3</td>
<td>.76</td>
<td>.08</td>
<td>4.56</td>
<td>1.42</td>
</tr>
<tr>
<td>4</td>
<td>.81</td>
<td>.16</td>
<td>5.59</td>
<td>1.28</td>
</tr>
<tr>
<td>5</td>
<td>.81</td>
<td>.22</td>
<td>4.64</td>
<td>2.09</td>
</tr>
</tbody>
</table>

Table 3. The respective amounts of positive or negative transfer occurring due to the treatment condition’s instructional regimen.

<table>
<thead>
<tr>
<th>Lesson</th>
<th>Percent of Positive (+) or Negative Transfer (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Near Transfer SM Exercise</td>
<td></td>
</tr>
<tr>
<td>Lesson 1</td>
<td>+13.73%</td>
</tr>
<tr>
<td>Lesson 1 Far Transfer SM Exercise</td>
<td>-0.6%</td>
</tr>
<tr>
<td>Near Transfer SM Exercise</td>
<td></td>
</tr>
<tr>
<td>Lesson 2</td>
<td>+4%</td>
</tr>
<tr>
<td>Lesson 2 Far Transfer SM Exercise</td>
<td>+21.89%</td>
</tr>
<tr>
<td>Near Transfer SM Exercise</td>
<td></td>
</tr>
<tr>
<td>Lesson 3</td>
<td>+13.09%</td>
</tr>
</tbody>
</table>
Table 3 Continued

| Lesson 3 Far Transfer SM Exercise | +5.75% |
| Lesson 4 Near Transfer SM Exercise | +32.44% |
| Lesson 4 Far Transfer SM Exercise | +44.43% |
| Lesson 5 Near Transfer SM Exercise | +46.64% |
| Lesson 5 Far Transfer SM Exercise | +3.89% |

Transfer formula

\[
\text{Transfer} = \frac{\text{Treatment Group Score} - \text{Control Group Score}}{\text{Total Possible Score} - \text{Control Group Score}} \times 100
\]

Figure 1. Transfer formula no. 5 discussed in Gagné, Foster, and Crowley (1948).

Research Question 2: How is the amount of and type of cognitive load imposed upon participants affected during their engagement with the adapted 4C/ID instructional regimen?

The answer to this question required an examination of the cognitive load levied upon the participants by the full videos, partial videos (treatment condition only), design intent videos (treatment condition only), near transfer SM exercises, and far transfer SM exercises associated with each lesson as well as the calculation of the learning efficiencies and instructional efficiencies of each lesson using standardized versions of the performance scores and cognitive load scores. The cognitive load scores for the videos are displayed in Figures 2 and 3, and Table 2 displays the cognitive load scores corresponding to the near transfer SM exercises and far transfer SM exercises. The participants in both conditions
experienced fairly low amounts cognitive load while viewing the full videos albeit the full videos for Lessons 1, 2, and 5 caused the treatment condition participants to experience a little more cognitive load than the participants in the control condition. This effect was reversed for Lessons 3 and 4. The partial videos caused relatively low levels of cognitive load, whereas the design intent videos caused a moderate amount of cognitive load during Lesson 3 and 5. The performance and cognitive load of both condition’s participants were examined in an aggregate fashion using instructional efficiency and learning efficiency where the source of cognitive load for instructional efficiency came from the near transfer SM exercises and far transfer SM exercises, respectively, and the source of cognitive load for learning efficiency came from the participants’ experience viewing and following along with the full videos. Therefore, there were a set of efficiencies (instructional and learning) associated with the near transfer SM exercises and a corresponding set of efficiencies (instructional and learning) associated with the far transfer SM exercises. Table 4 presents the instructional efficiencies and learning efficiencies of each lesson (for examples of the instructional efficiency and learning efficiency formulae applied in this study see van Gog & Paas, 2008). The treatment condition observed more instructional and learning efficiencies above zero than the control condition with both the near transfer SM exercises and far transfer SM exercises. In order to understand any possible relationships between the cognitive load and transfer observed, the authors considered the correlations between the efficiencies and the amount of transfer achieved by the treatment condition participants. Near transfer SM exercise instructional efficiency shared a strong positive correlation with the amount of transfer ($r=.789$) while the near transfer SM exercise learning efficiency shared a
weak positive correlation with the amount of transfer ($r = .351$). Although the far transfer SM exercise instructional efficiency was not correlated with the amount of far transfer achieved ($r = -.008$), the far transfer SM exercise learning efficiency and the amount of transfer shared a weak positive correlation ($r = .421$).

![Full Video Cognitive Load Scores](image)

*Figure 2. Graph of the cognitive load scores from each lesson’s full video by experimental condition.*
Figure 3. Graph of the cognitive load scores from each lesson’s partial videos and design intent videos (treatment condition only).

Table 4. The instructional efficiencies (IE) and learning efficiencies (LE) associated with each lesson’s near transfer SM exercise and far transfer SM exercise displayed by condition.

<table>
<thead>
<tr>
<th>Lesson</th>
<th>Near Transfer SM Exercise</th>
<th>Far Transfer SM Exercise</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IE</td>
<td>LE</td>
</tr>
<tr>
<td>1</td>
<td>-.07</td>
<td>.17</td>
</tr>
<tr>
<td>2</td>
<td>.17</td>
<td>.29</td>
</tr>
<tr>
<td>3</td>
<td>-.09</td>
<td>-.21</td>
</tr>
<tr>
<td>4</td>
<td>-.06</td>
<td>.10</td>
</tr>
<tr>
<td>5</td>
<td>.47</td>
<td>.37</td>
</tr>
<tr>
<td>Treatment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-.09</td>
<td>-.21</td>
</tr>
<tr>
<td>4</td>
<td>-.06</td>
<td>.10</td>
</tr>
<tr>
<td>5</td>
<td>.47</td>
<td>.37</td>
</tr>
<tr>
<td>Control</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-.25</td>
<td>.38</td>
</tr>
<tr>
<td>2</td>
<td>-.96</td>
<td>.09</td>
</tr>
<tr>
<td>3</td>
<td>-.24</td>
<td>.33</td>
</tr>
<tr>
<td>4</td>
<td>-.03</td>
<td>-.04</td>
</tr>
<tr>
<td>5</td>
<td>-.46</td>
<td>.24</td>
</tr>
</tbody>
</table>
Discussion and Conclusion

The purpose of this study was to investigate the efficacy of an instructional regimen for SM instruction adapted from the 4C/ID model that structured WEs in manner that attempted to reduce ECL, actuate GCL, and facilitate near and far transfer for SM tasks. In order to address the research questions posed by this investigation, the performance of two experimental conditions was compared over the course of five consecutive lessons—the treatment condition that viewed full videos, partial videos, and design intent videos was assessed against the control condition which only viewed the full videos. The performance of both conditions on the near transfer SM exercises and far transfer SM exercises of each lesson as well as the cognitive load, instructional efficiency, learning efficiency, and the amount and type of transfer experienced by the participants was evaluated.

Throughout the study, the participants in the treatment condition maintained better performance than the control condition on all of the near transfer SM exercises and far transfer SM exercises, although the treatment condition maintained only slightly higher scores than the control condition on the Lesson 1 and Lesson 5 far transfer SM exercises. The instructional regimen (i.e., the treatment) facilitated varying amounts of positive transfer on the near transfer SM exercises with greater levels of positive transfer being observed for the treatment group’s performance on the Lesson 4 and 5 near transfer SM exercises. There was also a substantial amount of positive transfer present for the treatment condition’s performance on the Lesson 2 and 4 far transfer SM exercises whereas for all of the other far transfer SM exercises positive transfer only occurred in small amounts. These results suggest that the instructional regimen was appropriate for assisting participants in the treatment
condition with generalizing the knowledge that they had acquired in near transfer SM exercises. Regarding the instructional regimen’s capability to influence far transfer, the results were more mixed.

While viewing the full videos, each condition reported low levels of cognitive load. In addition, the treatment group reported low levels of cognitive load while viewing the partial videos and design intent videos. Both conditions experienced relatively low levels of cognitive load (e.g., “rather low mental effort” and “low mental effort”) while completing the near transfer SM exercises but a spike in the treatment condition’s cognitive load was observed during the Lesson 4 near transfer SM exercise. With regard to the far transfer SM exercises each condition experienced a steady increase in cognitive load from Lesson 1 through Lesson 3 (e.g., from “rather low mental effort” to “rather high mental effort”) but the treatment condition’s participants continued to see that increase during Lessons 4 and 5 whereas the control condition’s cognitive load began to subside to lower levels during these same lessons. This means that the treatment condition found the far transfer SM exercises to be more cognitively taxing or demanding as they proceeded through each lesson which could have been due to the modeling processes required by the tasks (i.e., more complex modeling procedures were required to complete the far transfer SM exercises in the later lessons). The execution of complex or intricate modeling procedures requires that the participant recognize and understand the deep structure of the part under consideration and how to aggregate smaller discrete modeling procedures into bigger ones and anticipate the outcome of a bigger procedure’s application. When this aggregation process is somewhat suppressed by schemata that have not been automatized it has the potential to cause a learner to have to hold several
disparate elements of the SM task in WM leading to an increased amount of cognitive load. In the case of the treatment condition’s performance on the Lesson 4 and Lesson 5 far transfer SM exercises the participants were required to execute tasks that had unfamiliar deep structures and when this was combined with their lack of cursory schemata application the amount of cognitive load that they experienced increased.

The instructional efficiencies and learning efficiencies produced by each lesson provide more insight into the underlying mechanisms by which the efficacy of the instructional regimen can be considered. For the near transfer SM exercises, there were several lessons in which the treatment condition and control condition had learning efficiencies above one, but only the treatment condition had any instructional efficiencies above zero. For Lessons 2 and 5 the treatment condition possessed combinations of a learning efficiency and an instructional efficiency above zero. For the far transfer SM exercises, the same type of relationship remained present where both conditions had several learning efficiencies above zero but the treatment condition had two lessons (i.e., 4 and 5) retain combinations of a learning efficiency and an instructional efficiency above zero, whereas the control condition observed this combination during Lesson 1 only. What can be ascertained from an exploration of the near transfer SM exercise and far transfer SM exercise efficiencies is the following: participants in both conditions experienced a minimal amount of ECL as revealed by the learning efficiencies above zero but it was primarily in the treatment condition where the surplus cognitive load that remained as result was dedicated toward GCL and the subsequent acquisition of schemata and development of cognitive skills. Access to the partial videos and the design intent videos may have been responsible for this
phenomenon because both types of videos offered the treatment condition participants the opportunity to continue learning and refining SM techniques whereas the control condition did not have the option to further elaborate upon the knowledge that they had gained from the full videos. Colley and Beech (1989) alluded to this elaboration phenomenon when they suggested that cognitive skills were predicated upon prior knowledge acquired during domain learning. As the instructional regimen proceeded the SM knowledge that the treatment participants had acquired in previous lessons helped to organize the newer knowledge that they were gaining from the full videos, partial videos, and design intent videos into robust schemata that could be applied during the execution of their cognitive skills.

By inspecting the correlations between each near transfer SM exercise’s efficiencies and the amount of transfer attained for the corresponding lesson, and the correlations between each far transfer SM exercise’s efficiencies and the amount of transfer attained it becomes evident that several relationships exists between treatment condition’s efficiencies and the amount of positive transfer that was achieved with respect to efficacy of the instructional regimen (treatment). A strong correlation was present between the near transfer SM exercise instructional efficiency and the quantity of transfer achieved on the near transfer SM exercises and a weak correlation existed between the near SM exercise learning efficiency and transfer. A weak correlation also occurred between the far transfer SM exercise learning efficiency and the amount of transfer achieved on the far transfer SM exercises. These findings are important because they indicate something about the relationship shared by instructional efficiency and the extent of positive transfer that took
place in the context of this study – as instructional efficiency increased the amount of positive transfer increased possibly indicating that GCL was actuated and that the treatment condition’s participants were able to acquire schemata during their engagement with the instructional regimen and then appropriately apply the schemata while engaging in the near transfer SM exercises. This finding is reminiscent of the relationship expressed by van Merriënboer, Kester, and Paas (2006) regarding the ability of WEs to promote GCL. The positive relationship shared between the far transfer SM exercise learning efficiency and amount of transfer demonstrates that the reduced amount of ECL experienced by the treatment condition participants during learning may have allowed them to focus more on acquiring and abstracting schemata such that they could approach novel solid modeling tasks but since there was no relationship between the far transfer SM exercise instructional efficiency and amount of transfer this assertion remains inconclusive.

Of particular interest is the effect revealed by the MANOVA and how it relates to the efficacy of the instructional regimen. For the near SM transfer exercises, the treatment group scored markedly higher than the control group on both the Lesson 4 and the Lesson 5 near transfer SM exercises – both lessons covered advanced topics in solid modeling. In light of the high correlation between the near transfer SM exercise instructional efficiency and amount of transfer discussed previously, it stands to reason that the instructional regimen had a very beneficial effect on the treatment condition participants’ opportunity to experience GCL during learning, which allowed them to more efficiently acquire and consolidate the schemata related to the subject matter of each lesson and subsequently translate the schemata to the application of the cognitive skills necessary to complete each lesson’s near transfer SM
exercise. Exposure to the whole-task practice and part-task practice included in each lesson may have allowed the treatment condition participants to experience this effect. The earlier lessons were less complex than Lessons 4 and 5, and required less sophisticated SM procedures meaning that participants in the experimental condition and the control condition may have been able to adequately recognize the deep structures of the lessons’ near transfer SM exercises but as the complexity of the exercises and their respective SM procedures increased, the distinction between both groups’ performance increased. The full videos provided all of the participants with whole-task practice which caused them to consider the controlled and automatic aspects of each lesson’s SM demonstrations and tasks. The part-task practice of the partial videos enabled the treatment condition to perform certain aspects of their cognitive skills in a perfunctory manner facilitating more accurate and precise performance on the complex tasks included in the Lesson 4 and 5 near transfer SM exercises. Also, the amount of GCL experienced by the treatment condition may have reflected the level of complexity present in the near transfer SM exercises and led to better performance because the participants were acquiring the appropriate schemata to recognize the deep structures of the problems.

This study was limited by sample size and duration, with a larger sample size having the potential to increase the detection of effects or differences between the participants involved in this investigation. Administering this study within a longer duration of time would have provided more opportunities to explore learning trends relative to the instructional regimen, especially considering that only five lessons (i.e., five weeks) were examined. In addition, sequence effects were not explored (Reigeluth, 2007), meaning that
variations of the way in which the full videos, partial videos, and design intent videos were administered and arranged were not investigated.

When the results of this study are considered in their entirety, it is evident that the instructional regimen adapted from the 4C/ID model was capable of enabling the treatment participants to develop and successfully apply the cognitive skills associated with solid modeling i.e., they were able to take the domain-specific information about solid modeling that they had encountered during their engagement with the instructional regimen and translate it into schemata that guided their performance(s) while completing the near and far transfer SM exercises presented within each lesson. The instructional efficiencies associated with each lesson indicated that learning conditions were prime for the participants to experience GCL, leading to the translation mentioned previously. The positive transfer achieved on a majority of the lessons by the treatment condition is highly suggestive that cognitive skill acquisition took place during the administration of the instructional regimen. Thus, the instructional regimen was effective for SM instruction. The next course of action would be to administer the regimen during a whole academic term with more participants as well as manipulate the regimen in the context of other engineering coursework and disciplines. What also remains to be explored is the nature of the cognitive skills associated with solid modeling because this study only establishes that cognitive skills were developed and employed during the SM tasks charged to the participants. Any further research should utilize the same measures and metrics (e.g., amount of transfer, instructional efficiency, learning efficiency, etc.) presented in this paper and enhance their application by comparing more treatment conditions with varying levels of exposure to the instructional regimen.
prescribed in this study in order to better evaluate the regimen or other instructional regimens like it.
References


The Application of a Functional Interaction Model for Solid Modeling Processes
Abstract

This paper aims to examine how CAD users attempt to model mechanical parts during the engineering design process by proposing the Functional Interaction Model (FIM) as a means of exploring how CAD users interact with the geometric representation of a part during design modeling. The FIM framework is subsequently applied to a study of undergraduate engineering students’ performances on solid modeling tasks and Poisson regression is employed to evaluate how the FIM’s antecedents can be used to evaluate and characterize the participants’ interactions. The results indicate that the FIM framework appears to be a promising framework for understanding users’ solid modeling abilities and leveraging CAD technologies to make design tools more supportive.
Introduction

This paper presents a model from which to explore how individuals practicing engineering design interact with geometric representations (e.g., a solid model) in constraint-based solid modeling computer-aided design (CAD) software and how these interactions characterize the individuals’ understanding of design intent and its application(s) to modeled mechanical or engineering parts. The Functional Interaction Model for Solid Modeling Processes (FIM) originated from a synthesis of themes and postulates appropriated from the existing literature on internal representations and human-computer interaction, and the FIM framework attempts to offer an understanding of how the constituent elements of one’s execution of a (CAD) task results in differing levels of performance on the task and impacts the quality of the resulting solid model and ultimately influences the engineering design process. The robustness of a solid model is important because the engineering design process in industry is very iterative in nature with designers typically creating new, redesigned models on the basis of preexisting models (Bai, Gao, Tang, Liu, & Guo, 2011; Gerritsen, Gielingh, Dankwort, & Anderl, 2011). If a model is designed poorly then it will not be reusable, but if it is well designed then its existing features can be designated as part of a newly created model.

Engineering design also has a cognitive aspect to it and is considered an information processing activity, where the knowledge applied to modeling a part or product comes from: 1) external sources like schematics, 2) internal sources such as the designer’s mental model of the part, along with 3) a synthesis of the two sources (Bracewell, Wallace, Moss, & Knott,
2009). The advent of behavioral modeling technology within CAD programs has required that a greater understanding of how designers conceptualize CAD tasks be gained. This type of technology is capable of supporting engineering design by “capturing design intent and automating the iteration procedure necessary to find an optimum design solution” (Xu & Galloway, 2005, p. 397), thus markedly increasing the productivity of the engineering design process. Behavioral modeling technology also is able to recognize a designer’s modeling patterns (i.e., a series of interactions with the model) during the execution of a CAD task and aggregate this data such that the technology can better support the use of the CAD program (Moss, Cagan, & Kotovsky, 2004; Modi, Tiwari, Lin, & Zhang, 2011). This suggests that a consideration of how the designer manipulates and transforms the model (i.e., interacts with the model) becomes warranted. From this brief discussion about the status of engineering design practices in industry relative to CAD, it is clear that the creation of a part involves more than the mere execution of the CAD modeling task. It incorporates the designer’s mental model of the part as well as the embedding of this knowledge into the part itself.

Design Intent

Whenever design intent is discussed in the literature two things become apparent: 1) if it is addressed, it is from the standpoint of software operability (Chu & Hsu, 2006; Li, Langbein, & Martin, 2010; Pratt & Anderson, 2001) and 2) it is usually implied and not clearly or succinctly articulated. With regard to both issues, the literature presupposes the role of the designer, engineer, or the student creating a solid model relative to design intent as well as records no efforts to examine the amount and type of interactions that users have with their model or other geometric representations during the solid modeling process.
A solid model is an external representation, which according to Ertl, Kopp, and Mandl (2008) is a structure “displayed by physical symbols, objects or dimensions” (p. 1599) – specifically, a solid model can be considered an external representation of geometry or a geometric representation composed of a specific structure (e.g., fasciae, vertices, edges, etc.; Hoffman, 2005). According to Kim, Pratt, Iyer, and Sririam (2008) most, if not all, engineered parts that are created using CAD software have several things in common: construction history, parameters, constraints, and features. Construction history is defined as “the procedure used to construct the...model” (p. 760) and CAD programs such as Dassault SolidWorks (SW) display construction history in a linear and sequential format (e.g., SW’s FeatureManager Design Tree). Parameters and constraints are complimentary to each other and are integral to the construction of features – parameters are the dimensional variables that dictate what aspects of a solid model are permissible to update and constraints establish relationships with and between the geometric elements and the parameters of a model. A feature defines the shape and form of a part, and an engineered part consists of several features that incorporate parameters and constraints (Bertoline & Wiebe, 2007). Usually the creation of a part begins with defining the base feature, the initial geometry of the part, and a part’s subsequent features are either added to or subtracted from the base feature geometry.

Design intent, which is the intelligence or sophistication integrated into an engineered part during the modeling process (Kim, Pratt, Iyer, & Sririam, 2008), can also be considered as “a set of geometric and functional rules which the final product [has] to satisfy” (Choi, Mun, & Han, 2002, p. 14). Wei, Tieqiang, & Tao (2008) provided a more comprehensive definition of design intent by referring to it as “the relationship[s] among functions of
product, constraints, technique information and geometric information and it represents the decision of designers” (p. 783). Design intent governs how a part and the relationships between its features behave and maintain stability when subjected to the iterative modifications characteristic of the engineering design process used by many firms and manufacturers (Kimura & Suzuki, 1989). For example, if a part requires alterations after being reviewed by an engineer, that part’s features should update in a predictable fashion relative to its construction history, parameters, and constraints.

The application of design intent during the solid modeling process not only demands that an individual understands how to model a part, it also requires that they envision how a part will behave upon future alteration (Johnson & Diwakaran, 2011). As the constituent elements (e.g., constraints and parameters) of a part work in unison to maintain the part’s stability throughout iteration, the designer has to be able to conceptualize and anticipate the effects of changes to the part’s geometry and implicit structure.

*Mental Models*

Rynne and Gaughran (2007) have suggested that an associated cognitive or mental model was an absolute necessity for effectively using CAD as a design tool, and that the robustness of this internal representation could lead to the accurate and efficient application of design intent. Mental models are dynamic and elaborate internal representations informed by prior knowledge, perception, memory, and reasoning that initiate one’s approach to and performance on tasks (deVega & Marschark, 1996). They are capable of representing “individuals, events, and relations” (Johnson-Laird, 1980, p. 106), and phenomena as well as simulating actions and scenarios (Moray, 1998; O’Malley & Draper, 1992; Payne, 2003).
Schnotz, Bannert, and Seufert (2002) noted that mental models have inherent structural features in common with the objects, relations, and scenarios that they depict and represent. These analogical properties allow a mental model to be robust in the sense that both general and specific information can be retrieved from the mental model – it can produce prototypes of an object or situation as well as provide generalizations about objects or situations, and has the capability to compensate for a lack of external sources of information (Johnson-Laird, 2005; Peirce, 1985).

In order to examine mental models, knowledge elicitation (KE) techniques have been employed. Cooke (1994) classified KE methods into three categories: 1) observations and interviews, 2) process tracing, and 3) conceptual techniques. The methods that fall into the observations and interview category are unobtrusive because the techniques do not adversely influence or bias the behavior of the participants under study. Process tracing methodologies produce inferential data about the cognitive processes and knowledge underlying task performance. Usually process tracing techniques are employed alongside a participant’s execution of a task and this methodology produces two types of data: performance scores (e.g., accuracy, error, or latency on the task) and verbal expressions from the participant about their behavior. Chester (2002) suggested that in the case of tasks that involve software usage (e.g., CAD tasks), process tracing methods may incorporate the recording of participants’ performance using screen recording software such as Techsmith Camtasia™. Due to the nature of this study emphasis will be placed upon process tracing methods because they are not disruptive to the learners’ performance of CAD tasks. The third class of knowledge elicitation methods examines the structure of domains and concepts. Conceptual
techniques are indirect and generate graphical representations of the structure of a domain, the relationships between the concepts in that domain, and the strength of those associations (e.g., cognitive mapping and multidimensional scaling).

Cognitive task analysis (CTA) utilizes a combination of KE methods (e.g., task analysis with interviews) determined at the researcher’s discretion to “uncover the cognitive activities that are required for task performance in a domain to identify opportunities to improve performance through support of these cognitive activities” (Potter, Roth, Woods, & Elm, 2000, p. 317). A CTA begins with bootstrapping which has the goal of identifying the nature and structure of the knowledge used during task performance and gaining familiarity with the nomenclature, knowledge base, and procedures of the task (Annett, 2000; Bonaceto & Burns, 2007; Chipman, Schraagen, & Shalin, 2000; Hoffman & Militello, 2009). Next, KE methods are administered and information about cognition and task execution is extracted from the participants. Lastly, the inferences contained within the data are represented.

Crandall, Klein, and Hoffman (2006) recommended a novel approach to CTA that functions by utilizing experiment-like tasks and collecting data on participants’ performance. They suggested that these tasks come in two varieties: constrained processing (CP) tasks and limited information (LI) tasks. CP tasks are ones that are familiar to participants but the tasks have been altered or constrained in some form or fashion such as requiring the participants adapt a particular strategy to execute the task or by providing interference to the normal strategy or routine employed during performance of the task. LI tasks are problem-like in the sense that they only provide participants with incomplete information regarding a task and the participant has to complete the task on the basis of this information. After knowledge
elicitation and acquisition has taken place the data, which can be both qualitative and quantitative in nature, is examined and structured so that inferences about the underlying cognitive skills of the task can be made.

Interaction

Human-computer interaction (HCI) researchers have always been aware of the impact that mental models have on learners’ or users’ performance when they are using software and hardware (Carroll, 1997, 2003; Shackel, 2009), and Payne (2003) noted that “to use such artifacts requires some representation of the domain application of the artifact – the concepts the artifact allows you to represent and process” (p. 147), which suggests that one’s underlying cognition can be manifested via their interactions with computer programs. Interaction has typically been examined from instructional (e.g., multimedia learning) and visual representation perspectives where interactivity consists of a set of properties of the interactions in which learners engage. Instructional interactions are characterized by multi-directional communication (two-way communication at a minimum) between a learner and an instructional system, allowing learners to structure and adapt an information presentation (e.g., multimedia; Moreno & Mayer, 2007). Conversely, interactions with visual representations (e.g., geometry) are distinguished by a learner or user acting upon the representation with the representation updating in response. Interactions in this form enable the exploration, manipulation, and transformation of the representation and its components (Liang & Sedig, 2009). It is the latter kind of interaction that is the primary interest of the researchers.
The work of Liang and his colleagues investigated how learners interacted with visual representations in the form of complex geometric primitives in order to understand their properties and their research has led to the identification of some general attributes of those types of interactions (Liang & Sedig, 2009; Liang, Parsons, Wu, & Sedig, 2010; Sedig & Liang, 2006; Sedig & Liang, 2008). In their most recent study they suggested that interactions have a temporal nature, proposing the concept of flow which is “concerned with the duration of interaction with a representation…[and] is equally about the action performed on the representation, as well as the reaction given by the representation” (Liang, Parsons, Wu, & Sedig, 2010, p. 141). Flow can be continuous or discrete – continuous flow arises from uninterrupted action over a period of time while discrete flow occurs as multiple instances of actions within a time span. They found that participants who engaged in discrete interactions while using a geometric visualization computer program experienced better performance on posttests than participants who engaged in continuous interactions, and that these results were due to the ability of discrete interactions to foster deep, reflective thinking. This finding coincides with the interactivity paradox presented by Bucy & Tao (2007) and according to this phenomenon interactivity, and by extension interactions, has the potential to be beneficial or detrimental to learning and performance depending on its complexity. Interaction complexity relies on the purpose for which the interaction took place initially and is determined by the subsequent effects of engaging in the interaction (e.g., did the interaction result in a satisfactory or predictable outcome?; Janlert & Stolterman, 2010). Although the work of Ling and his colleagues pertain to geometric representations in the
context of mathematics education, it seems appropriate to translate some of their concepts to geometric representations in the context of CAD.

Summary and Research Questions

From this consideration of mental models and interactions with respect to CAD, it is apparent that an underlying relationship is shared by all three areas. One’s mental model conceptualizes how a part may be modeled, governing the actions that the user performs during the CAD process and their ability to anticipate a part’s behavior with regard to the constraints, parameters, and features that they have created. This design intent (or set of functional relationships) that is present within a part is dictated by how the user interacts with the geometric representation of the part (i.e., how they manipulate and transform the part) during its development. The design intent, therefore, determines the overall quality and stability of the part (Liang & Sedig, 2009; Roy & Bharadwaj, 2002). It stands to reason that if a user’s mental model of a part influences how they attempt to embed design intent when they model the part, then their interactions with the part could be examined in order to ascertain how they envisage the CAD process and effectively engage in it to fulfill these task goals. The following research questions on CAD and design intent emerge from this rationale: 1) How can the FIM framework be used to evaluate the interactions learners have with geometric representations in the context of CAD? and 2) Can the FIM framework effectively characterize those interactions?

FIM Framework

The Functional Interaction Model for Solid Modeling Processes, or FIM framework, originated from the researchers’ attempt to reconcile two discrepant classifications of users’
actions while engaged in modeling engineering parts. Ault (1999) suggested that solid models could be acted upon geometrically or topologically where the former type of manipulation refers to modifications of the size or shape of a model’s features, and the latter pertains to the creation or removal of feature elements (i.e., edges or faces). Wiebe, Branoff, and Hartman (2003) presented a taxonomy of solid modeling behaviors and classified these behaviors as either basic or advanced where both types of behaviors take into account the way(s) in which a solid model is constructed using features, parameters, and constraints and how these behaviors impact specific changes within the model. Basic behaviors consist of individual modifications that impact a model’s parameters or constraints, whereas advanced behaviors are serial in nature and are based “on multiple modifications, impact multiple constraints, or involve equation-driven constraints” (p. 6). While both frameworks allude to how a solid model may be acted upon, they do not make an effort to elaborate any further on the factors that surround these interactions such as the semantics of modeling or the level at which the model is being manipulated (e.g., base feature).

The FIM framework is composed of five antecedents that characterize interactions with a geometric representation that are intended to contribute to or produce design intent (see Figure 1). These FIM attributes all contribute to an interaction’s quality, and they are feature representation, locus, semantics, interaction complexity, and flow. The feature representation portion of the FIM framework classifies the three types of features that make up a solid model’s structure: primary, secondary, and tertiary. Primary features are essentially base features (the initial geometry of the part), and secondary features are the successive features that are created after the base feature. Tertiary features are superficial
elements that are typically incorporated into a solid model near the end of the modeling process such as fillets, chamfers, and circular and linear feature patterns. Locus refers to the centrality of a user’s interaction with a feature and loci can be indirect where the user primarily works within a sketch in order to modify the solid model or direct where the user alters the parameters of a feature (e.g., changing a feature’s end type and depth). It should be noted that in the FIM framework the feature representation component feeds into the loci component. This is because during the solid modeling process feature representations preclude the locus of an interaction. For example, a base feature will have a sketch (i.e., indirect locus) from which it is created, whereas a tertiary feature such a fillet will not have an associated sketch, causing it only to possess a direct locus.
Figure 1. The FIM framework and its constituent elements.

The remaining FIM components are dichotomous in nature (i.e., having two levels) and cover some of the user resources that advance the interaction. Semantics pertains to the kind of knowledge exhibited by a user during an interaction. According to Chester (2007), two types of knowledge account for one’s performance on a solid modeling task: command knowledge and strategic knowledge. Command knowledge is knowledge of a CAD program’s commands and tools, and the procedures to use them. On the other hand, strategic knowledge is general, goal-directed, and relates to the knowledge of the alternate methods by
which a CAD task may be accurately and efficiently executed. Strategic knowledge leads to a proficiency that allows learners to accurately decompose a CAD task such that the best and most efficient solution can be implemented (Bhavnani, John, & Fleming, 1999; Bhavnani, Peck, & Reif, 2008). Wiebe (2003) observed the distinction between both sets of knowledge when he conducted a two part study that examined participants’ performance in various CAD software packages. He found that strategic knowledge added to the robustness and consistency of the participants’ solid modeling practice and led to precision while command knowledge was more brittle and had the potential to be an impediment when participants were thrust into noticeably different CAD software. Interaction complexity serves to indicate the richness and implications of the participants’ interaction with a solid model. Benign interaction complexity indicates that an interaction involved several actions leading to a satisfactory result (e.g., inside a sketch creating several sketch elements and then successfully producing an extrusion from this complicated sketch). An interaction sequence comprised of many aimless and random actions ending in an undesirable outcome serves as evidence that non-benign interaction complexity has been encountered. Lastly, flow pertains to the instantiation of an interaction and its duration, a continuous flow suggests that the interaction had no pauses in action when creating a feature whereas a discrete flow implies that there were pauses between a user’s actions during an interaction (i.e., during feature creation). Flow will be assessed at the CAD model feature level.

Feature representation, locus, semantics, interaction complexity, and flow are the five factors that all constitute the FIM framework which seeks to characterize the qualities of interactions with geometric representations at an intrinsic level with the goal of
understanding a user’s performance on CAD tasks. Schwarz, Reiser, Davis, Kenyon, Achér, Fortus, Shwartz, Hug, and Krajcik (2009) acknowledged that interacting with any kind representation (e.g., a scientific model or an engineering part) allows one to attach meaning to that representation and begin to predict how that representation will behave under varying circumstances (cf., Oh & Oh, 2010). Design intent is about designating meaning within a geometric representation (Bidarra & Bronsvoort, 2000), and the FIM framework permits one to ascertain how this meaning is produced by users via their interactions. Next, the methodology of a study conducted to examine the application of the FIM framework to undergraduate engineering students’ CAD performances will be described.

Methods

The study is the analytical portion of a larger investigation that examined the efficacy of a solid modeling instructional regimen for undergraduate engineering students. During this study, participants in both a treatment condition and control condition were exposed to a set of video demonstrations of CAD tasks every week throughout the first half of an academic semester. The video sets differed depending on the experimental condition – the treatment group’s weekly video set consisted of a video fully demonstrating a solid modeling task (full videos), a video partially demonstrating a solid modeling task (partial videos), and a video demonstrating design intent practices (design intent videos) whereas the control group only watched the full videos. The current study considers the impact of the design intent videos given to the experimental group.

Participants. The participants were six individuals from two sections of an introductory engineering graphics course taught at a Southeastern university and they were randomly
selected from each section of the engineering graphics course. Their average age was 20.5 (SD=1.76) with one female and five male students. All of the participants had a very small amount of experience with any kind of CAD software. The treatment condition had n=3 and the control condition had n=3. One subject matter expert (SME), whose performance was used as a benchmark relative to the treatment and control groups’ performance, also served as a participant. He had over 15 years of experience using SM software and had worked in industry.

**Materials.** Dimensioned pictorials for two mechanical engineering parts were provided to participants so that they could model each part in a CAD program during the iterations of the study (see Figure 2 for the pictorials for both parts). Parts 1 and 2 were considered to be CP tasks because they required the participants to generalize previously learned solid modeling processes to mechanical parts that were markedly different from the ones that were demonstrated in the videos. The design intent videos emphasized design intent by presenting and demonstrating brief solid modeling activities that reinforced the process of embedding intelligence and functionality into a solid model.

**Apparatus.** An Apple Macintosh Mac Pro desktop computer loaded with Windows XP, Techsmith Camtasia™, and Dassault SolidWorks™ (SW) all were utilized during the administration of this study. SW served as the CAD program in which the participants modeled the aforementioned mechanical engineering parts and Techsmith Camtasia™ was used to screen record the participant’s performance while they were creating each part. A headset microphone was used to record any verbal dialog produced by the participants and this audio was fed into the screen recordings.
Study Design and Procedure

This study occurred over five weeks of an introductory engineering graphics course where each of the course’s two sections was randomly assigned to the treatment condition and control condition. Three individuals from the treatment condition and three individuals from the control condition were randomly selected as participants. The SME was chosen prior to the administration of the study. The dependent variables under investigation were the dichotomous components of the FIM framework: locus, semantics, interaction complexity, and flow. The level of each FIM component exhibited by the SME and the participants was noted, and the data from these variables produced frequency data. The total amount of time it took each participant to finish each engineering part, the average time it took them to complete part features, the total amount of pauses they took during their modeling process between creating features, and the average pause length (in seconds) also functioned as dependent variables.
SME. One of the researchers met with the SME and recorded his performance of Part 1 and Part 2 during the same meeting. During the SME’s execution of each part he verbalized what he was doing (i.e., thinking aloud) – these statements were parsed in order to corroborate the SME’s performance.

Treatment Condition. This group of participants received exposure to a design intent video every week throughout the study and each participant met with one of the researchers individually and had their solid modeling performance on Part 1 and Part 2, respectively, recorded on separate occasions. During the first meeting, each participant was asked to complete Part 1 and was told that they had an unlimited amount of time to model the part. After they completed Part 1, the participants were asked to verbally delineate their modeling process. This audio was also a part of the recording. At the next meeting the participants modeled Part 2 and afterwards described their process of doing so.

Control Condition. These participants did not receive exposure to the design intent videos but otherwise they followed the very same procedure as the treatment condition.

Results

Figure 3 displays Gantt process charts of the SME’s and the participants’ modeling process that include the amount of time that was taken by each individual to model Part 1 and Part 2 as well as the number of pauses taken between the creation of features for each respective part. The SME’s performance was used as a benchmark from which to evaluate the treatment group’s and control group’s performance, and it is evident that the SME modeled each part markedly faster than any of either group’s participants. Overall, everyone took less time attempting to complete Part 2 than they did for Part 1 and for both Parts 1 and
2, only one participant from each group successfully completed the model aside from the SME. Although more pauses occurred during Part 2, the lengthiest pauses between features took place in the treatment group’s performances while modeling Part 1. While modeling each part the SME averaged around a minute per feature (see Table 1). For Part 1, the treatment group tended to take longer to create features than the control group, on average, but this trend was somewhat inversed for Part 2. Most of the pauses for Part 1 appeared after the first feature was created whereas for Part 2, the pauses appeared around the middle of everyone’s modeling process when they were transitioning from creating the part’s flange and attempting to produce a feature pattern from it. These relationships held true, respectively, for the individuals that actually completed the parts, albeit they did not have as many pauses during Part 1 as they did during Part 2.

Part 1 consisted of mostly secondary features but almost all of the participants spent a greater portion of their time dealing with the primary feature, with the successive features taking less time to model. This was mainly the case because Part 1 required that the participants produce reference geometry in order to create an inclined face for one of the secondary features of the part which caused almost all of the participants to exhibit long durations of trial and error as they attempted to continue modeling the part. Regarding Part 2, it was the latter secondary and tertiary features that requisitioned most of the participants’ time since the finished part was predicated upon circular feature patterns. The individuals who finished Part 2 spent less time on the remaining features as they came closer to completing the part.
Figure 3. Gantt process charts of the SME’s and participants’ modeling processes with pauses included.

*Indicates that the individual fully completed the model.
Table 1
Mean feature creation times (sec.) by group.

<table>
<thead>
<tr>
<th></th>
<th>Part 1</th>
<th>Part 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>SME</td>
<td>81.8 (63.4)</td>
<td>55.8 (72.2)</td>
</tr>
<tr>
<td>T1</td>
<td>1483.5 (354.3)</td>
<td>134.7 (149.2)</td>
</tr>
<tr>
<td>Treatment</td>
<td>201.8 (208.2)</td>
<td>178 (160.9)</td>
</tr>
<tr>
<td>T2</td>
<td>244.3 (199.7)</td>
<td>259 (369.7)</td>
</tr>
<tr>
<td>C1</td>
<td>457.5 (273.7)</td>
<td>362.3 (397.7)</td>
</tr>
<tr>
<td>Control</td>
<td>141 (105.7)</td>
<td>156.2 (218.5)</td>
</tr>
<tr>
<td>C2</td>
<td>315.2 (345.2)</td>
<td>104 (100.6)</td>
</tr>
</tbody>
</table>

Figure 4 displays the frequency at which the individual components of the FIM framework were applied during the SME’s and participants’ interactions with Part 1 and Part 2 during modeling. The SME mostly utilized strategic knowledge while modeling both parts, only encountered benign interaction complexity, and created features by working with indirect loci. He consistently experienced a continuous flow during his interactions. The control group used more command knowledge than the treatment group for Part 1 but otherwise both groups remained matched in their instantiations of the remaining FIM components. For Part 2, the control group worked more with indirect loci and experienced more instances of discrete flow than the treatment group.

Since the locus (direct [D] and indirect [ID]), interaction complexity (benign [B] and non-benign [NB]), semantics (strategic knowledge [S] and command knowledge [C]), and flow (continuous [C] and discrete [D]) components of the FIM framework are dichotomous
in nature Poisson regression was used to analyze the effect(s) that the experimental conditions had on how participants instantiated the FIM components during their interactions with Parts 1 and 2 while engaged in the modeling process (Nussbaum, Elsadat, & Khago, 2008). In particular, each FIM component was regressed using generalized linear mixed models (GLMMs) assuming a Poisson distribution of counts and containing random subjects effects nested within experimental condition and fixed effects of experimental condition, Part modeled, and FIM component. All of the GLMMs had a $\chi^2/\text{df}$ ratio less than one which suggests that there was no evidence of any of the GLMMs exhibiting a lack of fit. There was a significant interaction between flow and experimental condition, $F(1,12) = 6.01, p = 0.0305$. This meant that the type of flow experienced by the participants was actuated differently depending on whether they were in the treatment group or control group — specifically, participants in the control group experienced significantly more instances of continuous than discrete flow when compared to treatment condition, $t(12) = -2.64, p = 0.0218$.

While there were no other significant interactions pertaining to the FIM components, two main effects were significant. It must be noted that Part (1 or 2) had no significant effect within any of the GLMMs. Overall, complexity had a significant effect, $F(1,12) = 14.81, p = 0.0023$, with all of the participants observed encountering more instances of benign complexity than non-benign complexity, $t(12) = 3.85, p = 0.0023$. Also, locus had a broadly significant effect, $F(1,12) = 17.57, p = 0.0013$, suggesting that participants in both groups spent the majority of their modeling processes working with indirect loci (e.g., sketches) as
opposed to direct loci (e.g., manipulating feature parameters), \( t(12) = -4.19, p = 0.0013 \).

These inferential results can also be qualified by examining Figure 4.

Figure 4. Bar graphs of the amount and type of instantiations of each FIM component during the SME’s and participants’ modeling processes for (A) Part 1 and (B) Part 2.
Discussion and Conclusion

The primary aim of this study was to develop the FIM framework and use it to examine the solid modeling processes of users and their interactions with geometric representations (i.e., solid models) during engineering design. Parts 1 and 2 both possessed a moderate amount of intricacy and required several sequential primary, secondary, and tertiary features to be created in order to complete each model. As might be expected, the SME was the only individual to exhibit a degree of elegance with regard to his performance on Parts 1 and 2 – he took roughly half the time it took the participants in both groups to model the parts, with a minimal amount of pausing between features. The treatment group and control group participants were much less methodical in their approach to modeling the parts as indicated by the amount and duration of their pauses. This suggests that the participants were not in a position to effectively apply strategic knowledge during their modeling processes – largely what they had at their disposal was command knowledge. If this fact is combined with the dominance of indirect loci, it becomes clear that sketching was a key determinant in the participants’ modeling process for both parts; students’ lack of efficient sketching performance clearly impacted modeling times. There were several instances where participants were unable to produce a feature correctly because their sketch was created incorrectly, lacking the proper parameters and constraints. This was counter to the finding that, overall, the participants encountered more benign interaction complexity than non-benign interaction complexity. Closer examination revealed that a number of participants worked their way through the modeling exercises by trial and error until they found an amicable solution.
The significance that underlies the interaction between flow and experimental
condition highlights the impact of the design intent videos on the treatment group. Their
interactions with their Part 1 and Part 2 models were more continuous than the control
group’s interactions potentially indicating that the design intent videos enabled the treatment
group to better execute feature creation to a certain extent. This execution effect was much
more pronounced when the treatment participants modeled Part 2, if the amount of time
taken to model the part’s secondary features is considered. In that part it was feasible to
aggregate sketch elements and feature elements in order to efficiently create new features.
The design intent videos may have given the treatment participants the proper
conceptualizations necessary to understand this aggregation of elements process and how to
use it to their advantage. This suggests that the treatment group was beginning to exhibit
design intent and apply it to their modeling process due to more robust mental models
enhanced by the design intent videos. While the treatment group had a higher ratio of
strategic knowledge to command knowledge interactions than the control group, this
difference was not significant.

The FIM, as a framework, was considerably sensitive to participants’ interactions
with their solid models and proved useful in characterizing the interactions of all of the
parties involved in this study. The quantitative analysis was parsimonious with a more
holistic, qualitative analysis of student modeling processes. It also proved useful in
characterizing the expert performance of the SME, as compared to the (relatively) novice
students. Locus, flow, and interaction complexity were all found to be significant constructs.
Semantics, although more deserving of qualitative exploration than quantitative inspection,
plays an important role in interactions with geometric representations. As this was an atheoretical and *a posteriori* approach to examining interactions with geometric representations, further research is needed to assess the reliability and validity of the FIM framework. What was also established by this study was the appropriate application of Poisson regression as a means of statistically analyzing the dichotomous frequency data produced by the FIM framework. Results also indicated the count data being analyzed in this study could have benefited from a larger sample size and/or longer study duration with more parts to model (i.e., a higher repeated measures count per participant). Based upon the results of this study, future research should apply the FIM framework to CAD user studies in order to determine where leverage points, factors of a task that can be infused with technology to support task performance (Hoffman & Lintern, 2006), exist in people’s solid modeling processes; and how CAD technology can better support the engineering design process. The FIM framework should also be applied to CAD educational research in order to more definitively understand how students are practicing solid modeling and where fallacies exist within their abilities to do so.

In this paper, the researchers have attempted to establish a basis from which to examine some of the tacit aspects of how individuals engage in the practice of solid modeling by proposing the FIM framework. It accentuates the need for more consideration of the user side of design intent and how it gets applied by the user during solid modeling. Although the results of this study suggest that the FIM framework is promising, it still needs further refinement over time in order to be as accurate, effective, and reliable as possible.
References


Conclusion

The purpose of this dissertation was to gain a better understanding of how SM instruction could be enhanced and how SM practices shaped students’ performances in an introductory engineering graphics course taught during the Spring 2010 semester. The results of this dissertation study were partitioned into two journal ready manuscripts that described complimentary and concurrent studies. Both manuscripts presented thorough and systematic methodologies and statistical analyses in an effort to offer insight into the intricacies of SM in the context of CAD education.

The first manuscript discussed how an innovative SM instructional regimen that used worked examples in the form of tutorial videos demonstrating SM tasks was administered and what effects on learning resulted. In particular, this study examined how the innovative SM instructional regimen affected participants’ cognitive load and performance on both near and far transfer SM exercises. This study also incorporated ad hoc measures for instructional efficiency, learning efficiency, positive transfer, and negative transfer that were all applied in order to determine the specific impact of the instructional regimen. The following results emerged: 1) the treatment instructional regimen was indeed effective for promoting positive transfer in the near transfer SM exercises as well as the far transfer SM exercises, although this effect was more pronounced for the near transfer SM exercises; and 2) a positive relationship appeared to exist between instructional efficiency and positive transfer regarding the near transfer SM exercises (cf., van Merriënboer, Kester, & Paas, 2006). These findings demonstrate that the instructional regimen was effective in actuating germane cognitive load during learning and promoting the acquisition and development of schemata. These
schemata, in turn, allowed the participants in the treatment condition to easily recognize the deep structures shared by the near transfer SM exercises and the SM tasks they had observed in the tutorial videos. This suggests that students in engineering graphics courses should observe multiple approaches to creating solid models that vary in technique before being charged with completing relatively challenging solid models. This is because the study has shown that this is a robust means of causing them to experience germane cognitive load and create appropriate schemata, thus promoting positive transfer.

The second manuscript proposed the FIM framework and detailed its origins and its application to the evaluation of the participants’ interactions with their geometry while engaged in SM processes. A subject matter expert (SME) and two groups of students participated in this study, having their SM performances individually examined on two separate occasions. The results indicated that the majority of the SME’s and participants’ interactions took place within sketches (i.e., indirect loci) as opposed to features, perhaps because the parts that they were required to model contained rather complex sketches. The flow by group interaction that was observed suggested that the design intent videos helped the treatment group participants deal with the intricacy of their models – these participants exhibited more of a continuous flow throughout their modeling processes, much like the SME. It is apparent that the treatment group participants had more robust mental models at their disposal because they were able to aggregate multiple sketch elements together and more efficiently model certain features in Parts 1 and 2 relative to the control group participants. Although the FIM framework needs further refinement, its application to engineering graphics coursework may provide CAD educators with the opportunity to
determine where fallacies and strengths exist within students’ SM processes and how best to assist them with conceptualizing and practicing SM.

Next steps include exploring the tracking data from the study that was not utilized in either manuscript and analyzing it using log linear and cluster analysis. This would be to determine if any differences existed in how the participants sequentially accessed the tutorial videos and what types of patterns are present within this data. I would also like to further elaborate upon the FIM framework and conduct studies with participants for a longer duration than the aforementioned FIM study in order to converge upon the appropriate components that need to be included in the FIM framework and to understand where differences lie in users’ interactions with solid models. Lastly, I would like to conduct a comprehensive study that uses the FIM framework to analyze the results of applying the SM instructional regimen discussed earlier to not only introductory, but also intermediate, and advanced engineering graphics courses.
Appendix
The Effects of Worked Examples on CAD Performance and Learning Efficiency

Prospectus: January 23, 2011
Chapter 1: Introduction

The US Bureau of Labor Statistics (2010) projects that employment opportunities for engineers will increase by at least 11% within the next ten years. There are several reasons why this is likely to occur: a) engineers tend to engage in research endeavors and long-term projects, b) many senior engineers with years of experience are retiring, c) engineers generate the ideas that form the basis for product and process improvements, and d) the continued globalization of the profession. Although the job demands of engineers are increasing in complexity and continue to expand, employers “expect their newly hired engineers or scientists to be able to ‘hit the ground running’”, thus students pursuing engineering degrees need more training to remain competent and competitive (Rodrigues, 2001, p. 181).

Concurrently, the demand for online instruction in universities and professional environments has systematically increased. The Sloan Consortium (Sloan-C), an organization dedicated to researching and advocating the availability and use of different forms of computer-mediated learning, has outlined three forms of mediated learning: web facilitated, blended/hybrid, and online (Allen & Seaman, 2010; Bourne, Harris, & Mayadas, 2005). The distinction between these types of learning is determined by the percentage of instruction that is delivered online i.e., web facilitated courses have between one and 29% of their content presented online whereas blended/hybrid courses have 30% to 79% of their instruction offered in a web-based format. Online learning has 80% or more of the course content introduced online. In a recent survey of higher education institutions that utilize online learning Sloan-C found that the use of online learning has increased by 17% (Allen & Seaman, 2010). This trend has been attributed to the current economic climate. In particular,
engineering education has benefited from the application of online learning to training as well as continuing engineering education (CEE). Baukal (2010) described the benefits of online learning for engineering education as being convenience in terms of location and scheduling, customizable instruction that is flexible and adapted to learners’ needs, and the frequency at which new knowledge regarding engineering theory and technology is available.

As _computer-aided design_ (CAD) software has replaced manual drawing in engineering curricula, the integration of online instruction for CAD courses has become very prevalent (Connolly & Maicher, 2005; Ou, Sung, Hsiao, & Fan, 2002). For example, Folkestad and De Miranda (2001) advocated the use of tutorial videos to demonstrate AutoCAD techniques for creating two-dimensional (2D) orthographic technical drawings. Branoff and Wiebe (2009) elaborated upon the use of tutorial videos and online learning for CAD instruction by integrating them into the hybrid sections of an engineering graphics course that taught drafting and solid modeling. Of the 72 undergraduate students that participated in the study, 67% of them expressed a preference for the way that the CAD instruction was delivered i.e., recorded movies of sketching techniques, voiced-over PowerPoint presentations, and screen-recorded video demonstrations of solid modeling using Dassault _SolidWorks_ (SW). The authors also assessed whether any learning gains occurred in the hybrid sections in comparison to sections of the same engineering graphics course taught in a traditional (face-to-face) manner. Using the final exam scores of students as a proxy for learning gains, Branoff and Wiebe (2009) found that the participants in the hybrid sections performed equally well on the final exam. They recommend employing hybrid learning for CAD instruction due to the flexibility of hybrid arrangements and the fact that student
engagement is given consideration because instructional materials (e.g., tutorial videos) can be designed to encourage good study habits.

**Constraint-based Solid Modeling**

CAD is employed by engineers to visualize and produce technology, including mechanical and electrical parts and machinery. The application of CAD to design problems can occur in a variety of ways, for example, an engineer can produce 2D technical drawings (i.e., engineering graphics) and layouts or use solid modeling to create 3D models of parts for physical output processes. Solid modeling allows one more analogously represent geometry more directly in three dimensions to “design a device, system, or process and simulate manufacturing, testing, and operation” (Jenison, 1997, p. 70) by enabling engineers and technologists to create virtual models and it uses engineering graphics as a means to communicate product design information within the engineering environment (Bertoline & Wiebe, 2007).

Constraint-based solid modeling differs from 2D CAD systems in the capabilities of the software and the requirements imposed on the user to produce a mechanical part. 2D CAD software packages have traditionally only allowed engineers to make schematics and engineering graphics of parts (e.g., drafting) for the purpose of communicating with machinists and other technologists, whereas solid modeling has enabled engineers to not only create engineering graphics, but 3D representations of parts and machinery as well as simulate the functionality of those parts. In order to effectively create, simulate, and manufacture a piece of machinery an engineer has to be able to understand the capabilities offered by the software and how to implement them.
Solid modeling has experienced widespread growth since the early 1990’s beginning with software packages such as Unigraphics and SW (Harris & Meyers, 2007), and is has been “widely used in education…primarily in existing engineering graphics courses” (Howard & Muso, 2006, p. 1). Within many collegiate engineering programs, solid modeling training has been assimilated into engineering graphics curricula and students gain exposure to it early on in their major(s). In this regard, constraint-based solid modeling training forms a key foundational area in engineering students’ requisite skill base. Rynne and Gaughran (2007) have suggested that having a robust mental model or internal representation can greatly enhance the solid modeling strategies used by engineers during the development of a product. They assert that most CAD training places more emphasis on the novelties (e.g., tools and features) of specific programs as opposed to giving an apt amount of attention to the development of solid modeling strategies and workflows. As a result, students do not receive the appropriate instructional support (i.e., scaffolding) to proficiently perform solid modeling tasks and they subsequently experience a high demand upon their working memory (i.e., cognitive load), which possibly prevents them from “developing a long range [solid] modeling strategy” (Wiebe, 2003, p. 26).

Frameworks

Some researchers and CAD practitioners have suggested that CAD education and solid modeling instruction is inadequately preparing students for the procuring gainful entry-level employment in the workforce because graduates do not have the skills that are necessary for meeting the demands of the engineering and manufacturing industries (e.g., constant modification and reuse of engineered parts) (Ahmed, 2007; Hamade, 2009; Ye,
Peng, Chen, & Cai, 2004). In order to meet those demands students must have a comprehensive understanding of how to apply and manipulate design intent using design tools such as SW (Hartman, 2004) but there have been no efforts presented within CAD literature that detail any exploration into how design intent can be effectively and overtly integrated into a solid modeling instructional regimen. Most training regimens focus learners’ attention on menu commands of specific design tools and utilize prototypical examples that do not require the learners to consider the advantages and disadvantages of a proposed modeling process – this leads to insufficient mental models and the acquisition of a limited set of skills that cannot be easily generalized to differing situations (Rynne & Gaughran, 2007). Rossignac (2004) attributes such fallacies to “the discrepancy between the elegant formulations promoted in scientific publications and the intuitive, often much simpler, mental models that are helpful when probing the validity of a solution, looking for counterexamples, or inventing proofs” (p. 1461). These *elegant formulations* do not necessarily promote students’ abilities to formulate design and engineering problems, use CAD to solve these problems, and understand modeling processes – it is a robust mental model that can encompass an understanding of both the design tool and design intent that facilitates these abilities (Hartman 2005; Wiebe, 2003). In Chapter 3 the author proposes a study that serves as an intervention that provides undergraduate engineering students with solid modeling instruction focusing on the practice of design intent and in order to address the concerns of this study the following themes, which are expounded in Chapter 2 along with their respective contributions to the investigation, will be examined: a) scaffolding, b) instructional design, c) mental models, and d) cognitive load.
Scaffolding addresses the *elegant formulations* (e.g., textbook modeling exercises that do not encompass a range of solution techniques) that have traditionally been a part of solid modeling instruction by discussing the benefits of worked examples, prototypes of expert problem solving processes that provide instructional guidance by modeling these processes (Renkl & Atkinson, 2010). Cognitive Load Theory dictates that any type of instructional regimen should consider the kind and amount of cognitive load (e.g., mental workload imposed by instruction) that is associated with it (Moreno & Park, 2010), and that the kinds of cognitive load that are detrimental for learning should either be reduced or counterbalanced by cognitive load that enhances learning. The *Four-Component Instructional Design Model* is an instructional design framework that can structure the presentation of worked examples and manage the cognitive load associated with instruction such that effective learning can take place (van Merriënboer, 1997) and it also facilitates the creation of robust mental models from which learners can derive problem solving strategies and solutions. The following subsections provide glimpses of each of the preceding themes that will be elaborated upon in the next chapter.

**Scaffolding**

*Scaffolding* is instructional support provided to learners in an effort to help them to solve problems that they would not have otherwise been able to complete on their own (Wood, Bruner, & Ross, 1976). Puntambekar and Hübscher (2005) delineated the key characteristics of scaffolding as being an ongoing diagnosis of a learner’s current level of understanding, calibrated support, and the gradual fading of that support. It can be administered in several forms depending on the needs of learner, soft scaffolding and hard
scaffolding (Belland, Glazewski, & Richardson, 2008). The former is considered to be “just-in-time support provided by a teacher or peer” and it encourages the learner to actively participate in the problem solving endeavor whereas the latter is administered tangibly in the form of computer-based or paper-based cognitive tools such as tutorial videos (p. 407).

Along with soft and hard scaffolds, modeling (i.e., the demonstration of problem solving processes) can serve as a means of scaffolding e.g., presenting learners with problems that focus their attention on certain aspects of the problem while not overburdening the learner with impertinent details. Scaffolding can be applied to CAD training as well, as Piegl (2005) noted, “people can learn much faster by seeing examples, that is, CAD design tools can be enhanced by design-by-example methods” (p. 466).

**Cognitive Load**

*Cognitive load* occurs due to the limitations of working memory i.e., any demand placed on working memory that has the potential to “impede skill acquisition” during the process of learning or executing a learning task can be considered a form of *cognitive load* (Chandler & Sweller, 1991, p. 294). Cognitive Load Theory (CLT) takes into account the effects and implications that instructional design and learners’ cognitive capacity have on their performance. The theory originates from two sources: Miller’s (1956) research on the capacity of working memory where he hypothesized that working memory is capable of holding between five and nine chunks of information at one time, and Sweller’s (1988) research on the efficacy of problem solving.

Three types of cognitive load exist: intrinsic load, extraneous load, and germane load. Intrinsic load is determined by the innate complexity of the learning task placed before a
learner and the amount of domain knowledge (i.e., expertise) that the learner has relative to the task. Extraneous load is the cognitive load imposed upon the learner by the design or format of the learning task, this kind of cognitive load can be manipulated (i.e., increased or decreased) by the instructional designer. Germane load is caused by effortful learning and tends to consist of the remaining cognitive resources not directed toward intrinsic load and extraneous load (Schnotz & Kürschner, 2007). All three kinds of cognitive load make a contribution to a learning task’s learning efficiency and instructional efficiency, measures that determine the efficiency of instructional conditions in terms of task performance, test performance, and cognitive load (van Gog & Paas, 2008). Both efficiency measures utilize the linear relationship that exists between cognitive load and performance (e.g., high learning outcomes co-occurring in conjunction with low cognitive load equates to high efficiency).

**Instructional Design**

Scaffolding can assist in decreasing the extraneous cognitive load imposed on learners by allowing the learners to focus solely on the critical aspects of a task or problem that need to be mastered, especially if *worked examples* or goal free problems are used. Worked examples provide learners with an expert’s model of problem solving in a step-by-step fashion i.e., attention is placed upon the problem states and the solution steps associated with the problem (Renkl, 2005). The *Four-Component Instructional Design Model (4C/ID)* proposed by van Merriënboer (1997) delineates how to structure instruction using scaffolding so that any extraneous cognitive load imposed on learners can be reduced as much as possible using worked examples. The framework dictates how to coordinate the constituent aspects of a learning task such that learning experience encompasses the fidelity of the
intended execution or performance of the task and promotes the synthesis of the constituent skills of the task (van Merriënboer, Kester, & Paas, 2006). 4C/ID separates instruction into whole-task practice which consists of “concrete, authentic…experiences” (p. 43), part-task practice which emphasizes the procedural or automatic skills required by the task, supportive information that allows learners to focus on the controlled aspects of the learning task, and just-in-time information aimed at automatizing the lower order skills required by task performance. The crux of 4C/ID lies in the use of worked examples in the contexts of whole-task practice (i.e., learning tasks) and part-task practice where whole-task practice makes a substantial contribution to learners’ construction and acquisition of schemata related to the performance of a task and part-task practice assists with strengthening the automatic skills that make up the task (van Merriënboer, Clark, and de Croock, 2002). Schema construction and acquisition also informs the creation of mental models which assists in reasoning about a domain and problem solving within it.

**Mental Models**

If attention is given to the design of CAD instruction and the subsequent cognitive load imposed on learners by the instruction it also becomes necessary to consider and understand what type of internal representations of the solid modeling tasks the learners are forming. The most likely internal representation to be created is a mental model, which is an elaborate and multifaceted internal representation that permits an individual to mentally simulate actions and scenarios (O’Malley & Draper, 1992). Mental models can be assessed using knowledge elicitation methods such as cognitive task analysis (CTA). CTA explores the cognitive strategies employed by individuals when they attempt to complete a task and it
attempts to describe the cognitive processes associated with the proficient performance of the task (Hoffman & Militello, 2009). Several authors have suggested that the enhancement of learners’ mental models of solid modeling tasks has the potential to lead to high levels of CAD proficiency. Rynne and Gaughran (2007) have suggested that robust mental models promote the efficient use of parametric modeling software. Similarly, Wiebe’s (2003) research on the semantic and syntactic aspects of parametric modeling indicated that the ability of CAD students to produce robust mental models was an important factor in their performance.

**Summary**

For the purpose of multimedia CAD training, all four frameworks under consideration share an interdependent relationship. For example, during his articulation of CLT Sweller (1988) came to realize the contribution that scaffolding can make to the reduction of cognitive load and the importance of instructional design because he asserted that scaffolding in the form of worked examples (i.e., goal free problems) enables the “rapid learning of essential structural characteristics” (p. 260) of problems and learning tasks. Worked examples function by allowing a learner to solve for a relatively small amount of unknowns within a problem as opposed to requiring learners to not only solve for unknowns but to continuously assess the differences between the current problem state and the goal state of the task which increases the amount of extraneous load (Wouters, Tabbers, & Paas, 2007). Recently, there has been an increase the incorporation of worked examples in web instruction (Atkinson & Renkl, 2007; van Merriënboer, Clark, & de Croock, 2002). By including scaffolding via worked examples in an instructional design framework such as 4C/ID
learners can appropriately form schemata from which they can build mental models (van Merriënboer, Clark, and de Croock, 2002). To date, the literature records only a handful of efforts to apply the 4C/ID model or any other instructional design framework to CAD instruction and no attempts to investigate the effects of CLT and mental models on learners’ solid modeling performance (Hartman & Branoff, 2005). Therefore it has become necessary to explore how these factors impact students’ abilities to understand and execute solid modeling tasks so that they can be better prepared to enter the workforce.

**Problem Statement**

With many engineering firms requiring that employees be well versed in *design intent* in the context of the standard CAD software packages used in industry, it has become necessary to train students more comprehensively. This study addresses these concerns by examining how students enrolled in two sections of GC 120 Foundations of Graphics can be effectively taught design intent through the use of fully and partially worked examples in the form of tutorial videos uploaded on the NCSU Wolfware *learning management system* (LMS). By having the students engage in solid modeling tasks and weekly knowledge assessments that supplement the videos as well as evaluations of the mental effort (i.e., extraneous cognitive load) imposed by the videos and modeling tasks the author will be able to determine the amount of instructional efficiency that the students experience. CTAs of a select set of students provide the means to analyze the trainees’ understanding of design intent. The findings of this study should help us understand how CAD instruction can be enhanced toward the goals of increasing instructional efficiency and more effectively presenting design intent.
Research Questions & Hypotheses

The research questions and hypotheses center around how can CAD curricula be structured to effectively present the concept of design intent and promote instructional efficiency (i.e., learning conditions that lead to high performance outcomes while imposing low to moderate amounts of cognitive load on students). More specifically:

1. Do interactive videos for SW tasks that incorporate worked examples and remediation alter participants’ instructional efficiency i.e., produce learning conditions conducive to high learning performance outcomes and low cognitive load?
   a. H1: Participants using interactive videos incorporating worked examples and remediation should experience higher instructional efficiency than those not exposed to the same materials.

2. Does using interactive videos for SW tasks that incorporate worked examples and remediation facilitate near and far transfer (i.e., the flexible translation and generalization of previously learned CAD skills to novel CAD tasks)?
   a. H2: Participants in both the treatment and control conditions should have relatively equal performance on near transfer tasks whereas participants exposed to the interactive tutorial videos should have higher performance on far transfer tasks.

3. Do the participants’ mental models reflect an understanding of design intent?
   a. H3: Participants who use the interactive videos should have more robust mental models of how to embed and apply design intent in SW.
Definition of Terms

**Blended/Hybrid Learning:** A course having at least 30% and up to 79% of the content and instruction delivered in a web-based format.

**Computer-aided Design (CAD):** Technology used for the 2D and 3D visualization and physical output of products and machinery information.

**Cognitive Load:** The demand placed upon working memory that is either innate to the subject matter of the instruction (intrinsic load), imposed by the design of instruction (extraneous load), or contributing to learning (germane load) (Chandler & Sweller, 1991).

**Cognitive Task Analysis (CTA):** A method of knowledge elicitation aimed at exploring the cognitive strategies employed by learners during problem solving.

**Design Intent:** The intelligence or sophistication integrated into an engineered part during the modeling process (Kim, Pratt, Iyer, & Sririam, 2008).

**Four Component Instructional Design Model (4C/ID):** An instructional design framework that organizes learning around worked examples by utilizing whole-task training, part-task training, supportive information, and just-in-time information.

**Instructional Efficiency:** The linear relationship that exists between learners’ performance scores and cognitive load e.g., high performance scores and low cognitive load indicate high instructional efficiency whereas low performance scores and high cognitive load signifies low instructional efficiency.

**Learning Management System (LMS):** A consolidated set of software and hardware tools that support web-based teaching and learning applications.
**Mental Model:** A robust internal representation that allows an individual to mentally simulate actions and scenarios (O’Malley & Draper, 1992).

**Online Education:** A course having more than 80% of the content and instruction offered in a web-based format.

**Scaffolding:** Instructional support provided to learners in an effort to help them to solve problems that they would not otherwise have been able to complete on their own (Wood, Bruner, & Ross, 1976).

**Schema/Schemata:** A cognitive structure(s) that organizes knowledge and assists in problem solving.

**SolidWorks:** A parametric (i.e., dimension driven) CAD and solid modeling software package.

**Worked Example:** A prototype of expert problem solving processes and models these processes, and it consists of a problem formulation, solution steps and strategies, and the final solution (Renkl & Atkinson, 2010).
Chapter 2: Literature Review

In this chapter the underlying subject areas of this study’s research questions will be discussed. These areas or themes include: Computer-Aided Design, Expertise, Internal Representations, Multimedia Learning, Cognitive Load Theory, and Scaffolding. Encompassed in this discussion will be the constructs of these themes as well as the relationships and interdependencies shared between these themes. This chapter concludes with an explanation of how these subject areas inform the author’s investigation.

Computer-Aided Design

Engineering graphics, drawings and specifications for the creation of machinery and architecture, predates the fields of drafting and CAD by several millennia (Harris & Meyers, 2007). Engineering graphics has been in existence since 4000 BCE and the earliest known examples of engineering graphics are Paleolithic and Neolithic cave drawings, and Egyptian hieroglyphics. As the discipline of engineering gained prominence during the Industrial Revolution it became necessary to incorporate drafting into the design process as it facilitated the fluid and succinct communication of design specifications for the production of machinery and mechanical parts. By the 1970s computer-aided design, or CAD, began to supersede drafting because of the advent of computer technology. Hoffman (2005) characterized the two dominant CAD approaches of the era as being the constructive solid geometry (CSG) approach and the boundary representation (B-rep) approach. The two approaches both used 3D geometry and they only differed in the way that the geometry was interpolated by the computer and acted upon by the user. Although CSG utilized geometric
primitives (e.g., cubes, cylinders, and spheres) to create a mechanical part whereas B-rep made use of surface patches as the basis for complex geometry, both approaches made use of Boolean functions such as union, intersection, and difference. By the early 1990s a new 3D modeling approach, parameterized solid modeling, had become more prevalent. By the end of the decade, a number of related approaches converged around a common set of features and interface elements, commonly referred to now as constraint-based modeling.

Constraint-based solid modeling (hereafter simply called *solid modeling*) allows one to “design a device, system, or process and simulate manufactur[ing], testing, and operation” (Jenison, 1997, p. 70). The strength of solid modeling lies in its ability to uses engineering graphics as a means to communicate product design information within the engineering environment (Bertoline & Wiebe, 2002). It synthesizes drafting and 3D modeling, and introduces parameterization into the modeling process through the use of dimensions and geometric relationships (i.e., constraints). According to Kim, Pratt, Iyer, and Sririan (2010) most, if not all, engineered parts that are created using solid modeling have several things in common: construction history, parameters, constraints, and features. Construction history is defined as “the procedure used to construct the…model” (p. 760) and many constraint-based solid modeling programs, such as SolidWorks (SW), display construction history in a linear and sequential format (e.g., SW’s FeatureManager Design Tree). Parameters, dimensional variables (e.g., length, height, and diameter) that dictate what aspects of a solid model are permissible to change and update; and constraints, relationships established with and between the geometric elements and parameters of a model, are complimentary to each other and are integral to the construction of features. A feature defines the shape and form of a part, and an
engineered part consists of several features that incorporate parameters and constraints (Bertoline & Wiebe, 2002). Usually the creation of a part begins with defining the base feature, the initial geometry of the part, and a part’s subsequent features are either added or subtracted from the base feature. Parts that make up a piece of machinery can be brought together in assemblies that allow designers and engineers to simulate the functions of the machine.

A key component involved in solid modeling is design intent, which is the intelligence or sophistication integrated into an engineered part during the modeling process (Kim, Pratt, Iyer, & Sririam, 2008). Choi, Mun, and Han (2002) defined it as “a set of geometric and functional rules which the final product [has] to satisfy” (p. 14). Design intent governs how a part and the relationships between its features behave when subjected to the iterative modifications characteristic of the design processes used by many engineering firms and manufacturers (Kimura & Suzuki, 1989). For example, if a part requires alterations after being reviewed by an engineer, that part’s features should update in a predictable fashion relative to its construction history, parameters, and constraints. Bertoline and Wiebe (2002) referred to this phenomenon as capturing design intent—the process of defining features of a part such that any subsequent modifications of the model would accurately reflect the original intent of the engineers that designated the part’s specifications (p. 140). Elaborating upon the concept of capturing design intent, Wiebe, Branoff, and Hartman (2003) discussed dynamic modeling, the process by which the underlying logic of a solid model (i.e., design intent) can be evaluated. Dynamic modeling translates into how well a solid model can be iterated upon during the modeling process. The authors also presented a taxonomy of solid
modeling behaviors that constitute design intent, classifying these behaviors as either basic or advanced. Both types of behaviors take into account the way(s) in which the solid model is constructed using features, parameters and constraints, and how these behaviors impact specific changes within the model. Basic behaviors consist of individual modifications that impact a model’s parameters or constraints, whereas advanced behaviors are serial in nature and are based “on multiple modifications, impact multiple constraints, or involve equation-driven constraints” (p. 6). The changes that either type of behavior can cause takes the form of either geometric changes or topological changes, where the former refers to alterations in the size or shape of a model’s features and the latter pertains to the creation or removal of feature elements (i.e., edges or faces) (Ault, 1999). In the context of SolidWorks, a geometric change might include altering the diameter of a hole after the feature associated with parameter has been created while a topological change would be deleting a feature all together. Although design intent is inundated with complexity, it forms the foundation of a CAD trainee’s skill set/competencies and plays a central role in CAD education (Branoff, Hartman, & Wiebe, 2003). In particular emphasis is placed on design intent when CAD instruction focuses on feature creation, assemblies, and dimensioning.

Some solid modeling practitioners (e.g., design engineers, CAD instructors, and manufacturers) have suggested that CAD education is need of improvement due to the ever-changing demands of the manufacturing and engineering industries. Similarly, several authors have advocated for reform in terms of the training regimens offered by collegiate engineering programs. Ahmed (2007) conducted phone interviews with 26 CAD professionals to determine what pre-requisite competencies were necessary for entry-level
engineers seeking employment at CAD firms. The results of his study indicated that
engineering employers and CAD firms most valued process knowledge, knowledge about the
design process or specific design methodologies. Other professionals have conducted similar
research and have made comparable arguments, believing that current CAD curricula are
inadequately preparing students for the engineering workforce. Ye, Peng, Chen, and Cai
(2004) surveyed over 150 CAD professionals holding a variety of roles in the manufacturing
and engineering industries (e.g., CAD users, application and software developers, and
managers) about what skills and training needed to be incorporated into CAD curricula. The
survey responses indicated that the majority of the participants thought that more emphasis
should be placed on mathematics (e.g., analytical geometry) and CAD design methodologies
(e.g., constraint-based modeling) because these areas are critical to enhancing students’
abilities to formulate engineering problems, use CAD in solving these problems, and
understand design processes. Hamade and Artail (2008) elaborated upon Ye, Peng, Chen, and
Cai’s (2004) study by investigating the association between learners’ technical background
(i.e., the fundamental skills that form basis for mechanical design and CAD usage) and their
performance on CAD tasks. A 41-item questionnaire was administered to 44 mechanical
engineering seniors that inquired about the learners’ mathematical (general and specific to
CAD), graphical, mechanical design, and computer science skills relative to CAD and
engineering. The authors found that significant correlations existed between the participants’
mechanical design abilities and graphic abilities, and their CAD performance. There was also
a high correlation between the participant’s basic mathematical abilities and CAD
performance. This particular relationship appeared to be sound because of the general
problem solving skills that mathematics (e.g., calculus, differential equations) promotes. The line of inquiry presented in the preceding studies suggests that CAD education is interrelated to both allied discipline areas such as mathematics and to general abilities such as spatial visualization and problem-solving.

Researchers and educators have also explored how industry needs can drive the content presented in CAD curricula. Ault and Giolas (2005) have attempted to investigate the practices employed by CAD professionals and how these practices can inform CAD education. Of the mechanical designers and engineers that they interviewed for a glimpse of industry practices and the solid models of parts that were assessed, Ault and Giolas found that the designers strived for parsimony of features (i.e., the use of the minimal amount of features to create a part), that design intent should be an intuitive aspect of the design process, and that CAD software can be used not only to model a part but also during the planning and designing phases of a part’s development because CAD facilitates the efficient creation of variations of a part. CAD education needs to critically examine the state of the engineering and manufacturing industries and consider the challenges that students will face in the industry in order to ensure that they are competent as they enter the workforce (Branoff, Hartman, & Wiebe, 2003).

Although industry demands and requisite coursework impact the structure of CAD education, another factor that deserves consideration is the mental models of CAD tasks that are formed by learners. It has been suggested that robust mental models facilitate the efficient use of solid modeling software, especially in context of envisioning how a part should be created prior to executing or modeling it (Rynne & Gaughran, 2007). Wiebe (2003)
investigated how students’ mental models of the interfaces of constraint-based software packages affected their performance on CAD tasks. The two part study explored how CAD knowledge acquired by students was generalized and applied in differing solid modeling software packages (e.g., SW, AutoCAD, and Pro/E). Wiebe differentiated between the semantic and syntactic levels of information that exist within any given CAD package, proposing that the semantic level pertained to the commands that can be executed in the program whereas the syntactic level is concerned with the way that the program’s interface is structured (p. 16). In the first part of the study, participants modeled a valve in Pro/E and later asked to remodel the same valve in SW. Pro/E and SW were deemed to be semantically similar yet syntactically different. The second portion of the study followed the same procedure as the first part and required a different set of participants to model the valve in AutoCAD and then later remodel the valve in SW. AutoCAD and SW were found to be both semantically and syntactically different. Aside from assessing the accuracy of each valve model from both groups of participants, each participant’s model completion time was evaluated and concurrent verbal protocol parsed. Wiebe (2003) found that better knowledge transfer occurred in the first component of the study where both solid modeling programs were semantically similar (i.e., shared similar commands) rather than in the study’s latter segment where the programs shared no commonalities. This is exemplified by two things: the shorter modeling sequences and times employed by the first group’s participants; and his recommendation that CAD instructors teach students the commonalities between several solid modeling packages in order to promote transfer.
After considering the effects of CAD instruction on learners’ internal representations (mental models) of solid modeling tasks and their subsequent performance on these tasks, the various ways in which CAD education can be presented and delivered deserves attention. In his article *Ten Challenges in Computer-Aided Design*, Piegl (2005) suggested that “people can learn much faster by seeing examples, that is, CAD design tools can be enhanced by design-by-example methods” (p. 466). A review of the research on scaffolding may provide a basis for examining how worked examples can be incorporated into CAD instruction. The delivery methods for this type of instruction have been evolving with the needs of learners. e-Learning – instruction delivered digitally (e.g., web-based) using text, pictures, and sound – is one means that is currently employed by collegiate CAD and engineering programs to deliver on demand instruction to students (Mayer, 2003). The strength of e-Learning lies in its ability to leverage different instructional strategies to be presented to learners. Clark and Mayer (2008) noted that e-Learning can be used to format worked examples and make them interactive, potentially leading to greater learning gains. Folkestad and de Miranda (2001) applied both e-Learning and worked examples to CAD instruction by creating screen captured movies demonstrating AutoCAD tasks. Their study utilized a treatment condition with screen captured movies while participants in the control condition used a tutorial book. During the administration of the study participants in both conditions were required to complete tutorial exercises as well as independent CAD drawing assignments. Folkestad and de Miranda found no significant differences between each group’s performance on the pretest and posttest, test sensitization may have been a limitation as the same test was used in both instances of testing. Connolly and Maicher (2005) have iterated upon a web-based tutorial
program that they originally developed to teach learners about multi-view part drawings by incorporating feedback mechanisms and adding more interactivity and visualization capabilities to the tool. Other researchers have proposed that CAD can be practiced in a web-based environment (Ou, Sung, Hsiao, & Fan, 2002).

Summary

CAD instruction is in need of change and many practitioners have advocated that this reform begin with the consideration of the requisite skills and attributes that are necessary for students to be able to competently perform solid modeling tasks. Some researchers have suggested that the subject matter that surrounds engineering education requires more emphasis and integration into curricula so that learners may attain the fundamental capacities to execute tasks common to fields of design and engineering. Others believe that industry needs must dictate the structure and content of CAD curricula, as students must be adequately prepared to enter the workforce. Regardless of their stance on the future direction of CAD instructional strategies, practitioners do agree that possessing accurate mental models of the solid modeling challenges placed before a designer is very beneficial, and that understanding design intent is an important component of CAD instruction. Hartman (2004) shadowed and interviewed five professional engineers, revealing that expert CAD usage is demonstrated by the degree of design intent that is embedded in a solid model. As e-Learning takes on a more meaningful role in engineering education as a method of presenting and delivering instruction worked examples (e.g., screen recorded demonstrations of solid modeling exercises), this may become a potential means of improving CAD training and increasing students’ proficiency and ultimately their expertise. Chester (2007) and Bhavnani,
John, and Fleming (1999) alluded to the expertise that could result from proper CAD training. Two types of knowledge account for one’s performance on a solid modeling task, procedural knowledge and strategic knowledge. Procedural knowledge in the context of CAD is knowledge of a solid modeling program’s commands and tools, and the procedures to use them whereas strategic knowledge relates to the knowledge of the alternate methods by which a modeling task may be executed. Strategic knowledge leads to expertise and it is what allows learners to accurately decompose a CAD task such that the best and most efficient solution can be implemented (Bhavnani, et al., 1999). In the following section the subject area of expertise will be presented and how instruction can be structured to promote it will be discussed.

**Expertise**

This section provides a breakdown of the elements that constitute expertise and how learners can be trained in ways that increase their performance and proficiency on tasks. The section concludes with a presentation of the Four-Component Instructional Design (4C/ID) model and how it can be implemented. The expertise used during any task, including solid modeling tasks, can be derived from basic building blocks.

Expertise is defined as “the characteristics, skills, and knowledge that distinguish experts from novices and less experienced people” (Ericsson, 2006, p. 3) and pertains to “reproducible superior performance in a particular domain” (Lewandowsky & Thomas, 2009, p.141). Expertise can be acquired, it is not necessarily innate to the individual. It results from the deliberate practice of a set of tasks within a domain as well as experience, the
chronological amount of time that one spends on domain tasks. Charness, Krampe, and Mayr (1996) provided an estimate that between 1,000 and 10,000 hours of deliberate practice is required to attain expertise in a given area. According to Lewandowsky and Thomas (2009) deliberate practice has four distinguishing qualities: 1) it takes into account learners’ prior knowledge of the subject area; 2) it incorporates some type of immediate feedback mechanism (e.g., scaffolding); 3) it consists of repetitive performance of similar tasks; and 4) it is highly structured and intended to improve performance.

Research on expertise and its acquisition has traditionally been concerned with either the process(es) by which expertise is acquired or what type and level of performance occurs as a result of expertise, both lines of inquiry are prevalent within the literature (Farrington-Darby & Wilson, 2006). Chi (2006) described two methodologies commonly employed in expertise studies: 1) experts are studied in isolation with intent of modeling their performance and 2) the relative approach where experts are compared to novices in order to understand how expertise can be attained. Most studies use the relative approach and the subject matter of these investigations has ranged from the expertise in chess, baseball, physics, radiology, and mathematics (Feltovich, Pruetula, & Ericsson, 2006).

The effects of deliberate practice on performance for the purpose of developing expertise can be modeled using a learning curve (Jaber, 2006). Learning curves represent “the relationship between practice and [the] associated changes in behaviour” (Speelman & Kirsner, 2005, p. 3) and describe the increase in an individual’s proficiency for a task. Wright (1936) was one of the first individuals to articulate the learning curve. Initially, he investigated the manufacturing trends and economic factors associated with the production of
aircraft parts – specifically he examined the impact that production quantity of parts had on
the cost of the parts. Wright developed a curve displaying the relationship between overhead
(e.g., labor costs and hours) and the quantity of parts produced on the final cost of the part.
This curve has since been adapted to the prediction of learners’ performance on tasks where
the curve displays the effects that the relationship between time and the amount of deliberate
practice have on performance. Yelle (1979) suggested that there are mathematical functions
that learning curves follow – for example, the log-linear learning curve, the most commonly
used curve (Teplitz, 1991), includes parameters from which one’s learning rate and progress
ratio can be established. The learning rate is an exponential function of task performance
(errors) and task repetition, and the progress ratio is 1 minus the learning rate. As the
progress ratio increases (and the learning rate decreases) the slope of the learning curve
becomes steeper, which indicates that learning is occurring faster. It is typical for a curve to
demonstrate an increase in the progress ratio during the startup phase of the curve. Inherent
to most learning curves is an inflection point where learning or an increase in proficiency
seems to subside and the curve begins to level out, this is called the steady-state phase. The
steady-state phase represents the point at which learning ceases to continue (i.e., the learning
rate is equal to zero) and the individual maintains a constant state of task proficiency. Other
learning curve models include the plateau model, Stanford-B model, DeJong model, and the
S-model (Dar-El, 2000).

Another factor that underlies expertise is the ability to solve problems and no matter
the subject area, most problems have three defining characteristics: givens, goals, and
obstacles (Mayer, 1992). A given is the beginning state of a problem (e.g., the information
that frames the problem and also indicates what unknowns need to be solved for) and goals pertain to the “desired or terminal state of the problem” and the means and operations needed to get to the end state (Mayer, 1992, p. 5). Obstacles are the ambiguities of the problem that may possibly impede or prevent a learner from coming to a solution. Sternberg (2009) proposed a congruent problem structure that includes the initial state of the problem (a description of the unsolved problem), the set of operators (actions that can be used to solve the problem), the goal state (a description of the solved problem), and the solution (which is not immediately obvious). Problems generally are formatted in two ways, they can be well-defined or ill-defined, and experts differ from novices in the ways that they approach both well-defined and ill-defined problems.

Well-defined problems have obvious and easily identifiable solutions whereas ill-defined problems have vague problem spaces (i.e., the assortment of all possible actions and constraints that can be applied to the problem are vague) and lack clear pathways to a solution (Cropley, 1999). The distinction between a well-defined and ill-defined problem can sometimes be subtle relative to the individual attempting to solve the problem, an expert having at least an adequate amount of domain knowledge may perceive the problem as being well-defined and act accordingly whereas to a novice the same problem may be considered ill-defined and possess many ambiguous parameters because of the novice’s lack of or limited knowledge of the subject matter (Voss & Post, 1988).

Through the course of several experiments Yarlas and Sloutsky (2000) examined how experts and novices constructed representations of problems. They wanted to determine whether or not the problem representations of experts and novices differed because of the
content of their respective representations or as a result of the ways in which the representations were constructed. The results from their two studies indicated while novices focus on the surface features (e.g., cover story) of a problem when representing it experts give consideration to the deep structural principles of the problem. Both groups do encode the deep structural principles but novices have to deal with surface features and deep structural principles competing with each other due to a limited working memory capacity and because the surface features of a problem are more salient to them as a result of novices’ limited domain knowledge (Sloutsky & Yarlas, 2000). As novices gain more exposure to similar problems this effect begins to subside. Experts have a propensity to acknowledge the deep structure of problems and generally ignore the surface features.

The Four-Component Instructional Design (4C/ID) model dictates how training and instruction can be presented to learners so that they are better equipped to successfully engage in problem solving within a domain and develop expertise. The 4C/ID model originated from van Merriënboer’s research on instructional design and the development of the Apply Delayed Automation for Positive Transfer (ADAPT) model. ADAPT attempted to deal with transfer of learning in the context of robust training regimens, specifically the model examined how the knowledge and skills necessary to perform a particular task could positively influence a learner’s subsequent performance on related tasks (Jelsma, van Merriënboer, & Bijlstra, 1990). The premise behind the 4C/ID model is that the design of instructional regimens can be structured in a way that helps trainees engage in learning that requires the integration and coordination of cognitive skills in order to execute complex tasks and reach competency (van Merriënboer, Clark, & de Croock, 2002). This proposition lies in
opposition to what is offered by other instructional methods, most instruction has the
tendency to advocate the practice of skills and skill sets in isolation of each other and this can
result in inefficiencies in a learner’s performance. A skill is a goal-directed and well-
organized behavior acquired through deliberate practice, and these behaviors can come in
many forms (e.g., cognitive skills, motor skills, perceptual skills) (Proctor & Dutta, 2005). A
cognitive skill is a skill that is applied to intellectual, “knowledge-intensive” (VanLehn,
1996, p. 514), and rich learning tasks such as problem solving in a specific domain or realm
of subject matter and the acquisition and refinement of cognitive skills is one the focal points
of 4C/ID. There are four characteristics that make cognitive skills distinct from other types of
skills: 1) cognitive skills are comprised of both declarative and procedural knowledge, 2)
cognitive skills are acquired through training, 3) during acquisition the mental workload (i.e.,
cognitive load) imposed by the cognitive skill gradually gets reduced as the skill is mastered,
and 4) cognitive skills are applicable to a specific domain (e.g., cognitive skills in one subject
area do not easily translate into another domain) (VanLehn, 1996).

In the 4C/ID model, cognitive skills consist of two elements: non-recurrent skills and
recurrent skills (van Merriënboer, 1997). Non-recurrent skills are schema based and are
executed in controlled manner (i.e., these skills require conscious effort). Marshall (1995)
deﬁned a schema as a cognitive structure that represents knowledge and allows the
organization of knowledge and experiences such that an individual can discriminate between
similar and dissimilar experiences, “access a generic framework that contains the essential
elements of all of these similar experiences” (p. 39), and solve problems based on this
framework. As they possess both specific and generalized knowledge about a domain,
schemata are high flexible and serve as problem solving agents. Schemata are the mechanism by which non-recurrent skills can be performed in different ways depending on the problem situation (van Merriënboer, 1997). Recurrent skills are executed simultaneously to non-recurrent skills and are procedural in nature as they are performed accurately and quickly. They are automatic and can be strengthened, meaning that the likelihood that the recurrent skill will be applied correctly in the appropriate situation can be increased with practice (van Merriënboer, Jelsma, & Paas, 1992).

Instruction in 4C/ID is compromised of four components: whole-task practice (i.e., learning tasks), part-task practice, supportive information, and just-in-time information. Whole-task practice occurs within task classes where each task class contains several learning tasks arranged from simple to complex. Whole-task practice encompasses the cognitive skill under consideration as well as the non-recurrent and recurrent aspects of that skill. Learners perform tasks that require them apply and execute the skill in real and simulated conditions (e.g., a pilot in training may use a flight simulator to learn how to operate an aircraft). Whole-task practice also includes demonstrations and guidance intended to help the learners get acclimated to the task, this is termed supportive information. Supportive information helps enhance non-recurrent skills and can come in the form of worked examples, which display how an expert would go about solving a particular problem from beginning to end, or advance organizers that would help the learners to better conceptualize the information presented to them during whole-task practice. As whole-task practice proceeds the assistance (i.e., supportive information) provided to learner gradually fades so that the learner can perform the entire cognitive skill without any guidance. Part-task
practice is separate from whole-task practice and focuses on developing the automacity of recurrent skills as well as strengthening them. Just-in-time (JIT) information comes in the form of rules, step-by-step directions, and feedback for the execution of recurrent skills and can be presented during whole-task practice and part-task practice. When the 4C/ID is applied to training whole-task practice (in the context of a task class) occurs first and then part-task practice occurs subsequently. The whole-task practice includes supportive information and JIT information, and the part-task practice only includes JIT information. This workflow proceeds until all of the learning tasks in the task class are completed (van Merriënboer, 1997).

One of the goals of 4C/ID is transfer of learning, the generalization and extension of skills from one problem situation to another (van Merriënboer, Jelsma, & Paas, 1992). Transfer of learning is concerned with “how previous learning influences current and future learning, and how past or current learning is applied to similar or novel situations” (Haskell, 2001, p. 23). Gray and Orasanu (1987) observed that transfer happens as a result of analogical modeling, the process of mapping the structure of one complex task onto the comparable parts of a new task (i.e., aspects of the source problem space are transferred to the corresponding aspects of the target problem space). Several kinds of transfer exist and Haskell (2001) delineated six levels of transfer including nonspecific transfer, application transfer, context transfer, near transfer, far transfer, and displacement transfer. Of these levels near transfer and far transfer are of importance relative to the author’s proposed study. Near transfer happens when knowledge acquired from one situation is applied to a new yet similar situation and far transfer refers to the application of previous knowledge to a new situation
that is markedly different from the situation where the knowledge was acquired. Positive transfer and negative transfer were not mentioned in Haskell’s listing but are relevant as well. According to Sternberg (2009) positive transfer and negative transfer refer to relative difficulty under which transfer takes place, he suggested that positive transfer “occurs when the solution of an earlier problem makes it easier to solve a new problem” (p. 581) whereas with negative transfer occurs when solving a new problem on the basis of prior knowledge is difficult. The 4C/ID model is primarily concerned with near transfer and far transfer (van Merriënboer, 1997).

Lim, Reiser, and Olina (2009) tested the efficacy of the 4C/ID model by comparing the performance of pre-service teachers that engaged in whole-task practice to learn how to prepare grade books using Microsoft Excel to the performance of pre-service teachers that engaged in part-task practice to complete the same task. Lim and his colleagues found that whole-task practice made a more significant contribution to the participants’ performance than part-task practice on the grade book tasks because whole-task practice incorporates contextual interference and task variability. Contextual interference takes place when learners are presented with learning tasks where the knowledge and skills learned from one exercise interfere with the skills performed in previous exercises and the skills to be performed in future exercises. Contextual interference causes a learner to think and not to routinely solve problems. Task variability requires learners to practice non-recurrent skills in variation (i.e., learners are taught multiple ways to perform a skill). Both contextual interference and task variability contribute to the construction of schemata and lead to a more
comprehensive understanding of the cognitive skill under consideration (van Merriënboer, 1997).

Summary

Any learning task can be mastered to the extent that it can be repeatedly executed accurately and efficiently. Expertise is achieved once superior performance (based upon the standards of the domain) of the task exists. Learning curves are indicative of the rate at which expertise can be achieved as they consider the amount of deliberate practice that is involved to attain mastery of a skill or task. Hamade and his colleagues’ line of CAD research has attempted to establish a learning curve for CAD modeling tasks. Hamade, Artail, and Jaber (2007) found that students learn declarative CAD knowledge (e.g., menu commands in the CAD software) much quicker than procedural CAD knowledge (e.g., feature creation and modeling strategies) and that CAD tasks requiring more complexity (e.g., use of more operations and features) have a learning curve with high acceleration and a longer startup phase. They suggested that CAD training should place more emphasis on modeling strategies and that the CAD learning curve reaches its steady state phase (i.e., where the curve plateaus) as learners continue to model parts that utilize similar types of features (Hamade, Jaber, & Sikström, 2009).

It is plausible that the incorporation of an instructional framework into CAD education could enhance the learning curve for solid modeling processes. Hartman and Branoff (2005) asserted that an instructional framework for CAD training could increase the efficacy of the training and would allow students to construct the appropriate internal representations of modeling strategies necessary to engage in CAD tasks. The 4C/ID model
may be one training regimen that is applicable to CAD education as it emphasizes competency and transfer for instruction that takes place over varying amounts of time, from a minimum of several weeks to a year. The framework provides a systematic methodology to partition instruction into whole-task practice and part-task practice so that the non-recurrent and recurrent aspects of a cognitive skill can be mastered and proficiency in a learning task is attained. The literature records only a minimal number of efforts to apply any instructional design model to CAD training. The next section will discuss what internal representations are, how they can be explored, and what methodologies can be used to assess them.

**Internal Representations**

Fiore, Cuevas, and Oser (2003) suggested that there is a connection between one’s level of expertise and their internal representations, they believed that internal representations (e.g., mental models) are “associated with proficient task performance” (p. 186) because expertise begins with an understanding of the task and the knowledge corresponding to it. Internal representations are cognitive knowledge structures that are utilized in thinking and the construction of logic. They are informed by perception, memory, and reasoning, and internal representations initiate one’s approach to and performance on tasks and problem solving activities (deVega & Marschark, 1996). Internal representations can take on different forms and Johnson-Laird’s (1996) *triple-code hypothesis* outlined the three forms in which internal representations can appear as well as their characteristics. Propositional representations, mental images, and mental models compose the types of internal representations presented in the triple-code hypothesis.
A propositional representation is generated from verbal information and has “some sort of predicate-argument structure of an unknown syntax and lexicon, and...captures the explicit information conveyed by verbal assertions” (Johnson-Laird, 1996, p. 94). This type of internal representation contains descriptive information of a linguistic nature as well as connectives, qualifiers and quantifiers. Propositional representations are embodied in mental language that captures the meaning of the information and they can be translated from a mental language to a natural language (i.e., verbal spoken language) and vice versa (Johnson-Laird, Byrne, & Schaeken, 1992). Johnson-Laird (1996) and Intons-Peterson (1996) each proposed slightly different definitions for mental images. Johnson-Laird (1996) considered that a mental image is the perceived aspects of a situation or circumstance whereas Intons-Peterson (1996) thought that mental images were “sensory-perceptual memories with spatial features” (p. 34). Both definitions consider direct perception to be the basis upon which mental images are built but the latter definition reinforces the former by incorporating spatial information as a specific aspect of mental images. Johnson-Laird and Knauff (2002) conducted a series of experiments that all demonstrated that thinking can be adversely affected if mental images contain irrelevant or impertinent details about a problem situation. They observed that an individual may experience latency in reasoning due to an increase in cognitive load as a result of employing a faulty mental image during the execution of a task. The authors articulated this effect in their Visual-Imagery-Impedance Hypothesis which states that “relations that elicit visual images containing details that are irrelevant to an inference should impede the process of reasoning” (Johnson-Laird & Knauff, 2002, p. 364).
Propositional representations and mental images are encompassed within mental models (Johnson-Laird, 1980).

Craik first presented to notion of a mental model in 1943 and he postulated that it is a miniature model of the world and reality contained in an individual’s head that allows them to utilize prior knowledge, reason, and react (Johnson-Laird, 2004). Mental models are produced from perceptual, verbal, and visual stimuli and they represent “individuals, events, and relations”, and phenomena (Johnson-Laird, 1980, p. 106). They are dynamic, elaborate, multifaceted internal representations that are capable of representing various types of information and permit individuals to mentally simulate actions and scenarios (O’Malley & Draper, 1992). Several studies have been conducted that have examined mental models and their impact on subsequent performance. For example, Hegarty, Kriz, and Cate (2003) studied the effects that static diagrams and computer animations had on students’ mental models of mechanical systems and Branoff (1999) explored how coordinate information affected the mental model of 3D forms and the resulting students’ mental rotation abilities.

Schnotz, Bannert, and Seufert (2002) noted that mental models have inherent structural features in common with the objects, relations, and scenarios that they depict and represent. This occurs because mental models possess iconicity and have an analogical structure that enables information from the physical world to be abstracted and mapped onto the mental model (Johnson-Laird, 2005; Peirce, 1985). These analogical properties allow a mental model to be robust in the sense that both general and specific information can be retrieved from the mental model; it can produce prototypes of an object or situation as well as provide generalizations about those same entities. Mental models are informed by prior
knowledge and, in most cases, can compensate for a lack of external sources of information.

As mental models contain propositional representations and mental images, each type of
representation can be used to resolve discrepancies in the other (Johnson-Laird, 1996).

Mental models are also capable of being shared, meaning that in the context of a group of
individuals commonalities, may exist among the mental models of each individual (Klimoski
& Mohammed, 1994).

Human factors and organizational psychologists have suggested that in work
environments some tasks surpass the cognitive and performance abilities of a single person
and require a team of individuals to execute and complete it. Langan-Fox and Anglim (2004)
defined a team as “an entity with psychological significance above and beyond individuals”
(p. 337). In the context of a work environment an important factor regarding teamwork is the
interactions that take place between team members and it is these interactions that inform the
construction of team mental models, that is, the creation of a team mental model occurs
because of the convergence of each team member’s mental model(s) with those of the other
team members. A team mental model is the “team members’ shared, organized understanding
and mental representation of knowledge and key elements of the team’s relevant
environment” including the task, team, equipment, and situation (Mohemmed & Dumville,
2001, p. 90) and team mental models are capable of making communication and the
coordination of activities within the team more efficient, improving decision making and the
allocation of resources for subtasks, and enabling the team to formulate accurate teamwork
and task work predictions (Langan-Fox & Anglim, 2004).
As with any construct several methods of assessment and measurement exist for mental models. Knowledge elicitation is the process of collecting information relevant to a body of knowledge from a human source of knowledge (Hoffman, Shadbolt, Burton, & Klein, 1995). Cooke (1994) suggested that knowledge elicitation methods fall into three categories: 1) observations and interviews, 2) process tracing, and 3) conceptual techniques. The methods that fall into the Observations and Interview category are unobtrusive because the techniques do not adversely influence or bias the behavior of the participants under study. Observations require a researcher to record and document individuals’ behaviors and performance in natural settings in real time (i.e., as they happen) whereas interviews are retrospective as the information about a participant’s past experiences is sought after. Interviews can take place in an unstructured or structured format, the former interview format only has a topic area that will be discussed but no other predetermined content and the latter interview format is more systematic. The data produced from this category of knowledge elicitation methods is rich but superficial as the data consists of the direct reporting of verbalizable knowledge, that is, the data does not allow researchers much room to make inferences or generalizations about tacit knowledge. Cooke (1994) also placed task analysis in this category as the technique involves the observation of an individual’s behavior during the execution of a task. Task analysis and cognitive task analysis will be discussed in further detail later.

Process tracing methodologies produce inferential data about the cognitive processes and knowledge underlying task performance. Usually process tracing techniques are employed alongside a participant’s execution of a task and this methodology produces two
types of data: performance scores (e.g., accuracy, error, or latency on the task) and verbal expressions from the participant about their behavior (Cooke, 1994). These verbal expressions or protocols can be parsed and evaluated using verbal protocol analysis and subsequently validated against task performance. Verbal protocol analysis attempts to examine the cognitive processes underlying behavior and the execution of an activity, and this can be done using two methods: concurrent verbal protocols and retrospective verbal protocols (Ericsson & Simon, 1993). A concurrent verbal protocol, also known as think-aloud protocol, is elicited simultaneously with a task and the protocol requires the participant to retrieve information in short-term memory as they are reporting on their actions in real-time (i.e., immediately as they execute the task). Retrospective verbal protocol function in an opposite manner, they are administered immediately after the whole task is completed and require the participant to provide information from short-term memory and long-term memory about their cognitive processes during the execution of the task. Once either type of protocol has been recorded all of the verbal expressions in the protocol are transcribed and at least two transcripts are produced, one being a direct and unedited transcript and the other being an annotated version of the first transcript that breaks down the verbal phrases in the protocol by the activity (i.e., subtasks) being performed during the utterance (Kirwan & Ainsworth, 1992). Before any inferences can be drawn from the second transcript, the vocabulary spoken by the participant has to be iteratively reduced. Ericsson and Simon (1993) advised that each phrase or statement then be encoded in the following format: $R(x, y)$ where $R$ represents relations (e.g., the verbs and prepositions of the phrase) and $x$ and $y$ represent the arguments contained in the phrase. Lastly, inferences can be drawn from the
encoded transcript. Although both concurrent and retrospective protocols can be requested during a task, Kuusela and Paul (2000) recommended that retrospective verbal protocols be requested from participants because they do not require participants to simultaneously engage in a task while verbalizing their actions. On the other hand, concurrent verbal protocols do require simultaneous engagement, and the authors suggest that this strains participants’ working memory and imposes a mental workload upon them. Some researchers have mentioned that a dissociation or lack of correspondence may exist between task performance and the verbalizable knowledge that should be associated with the task (i.e., conscious task related information that is expressible in language) (Berry & Broadbent, 1984). This dissociation is characterized by participants’ inability to verbalize or articulate the rationale behind their actions during task performance as well as exactly what they learned as a result of completing the task (Sanderson, 1989). Eye tracking is a process tracing technique that does not produce verbal data but does facilitate inferences about task performance and behavior. Chester (2002) suggested that in case of tasks that involve software usage (e.g., CAD tasks), process tracing methods may incorporate the recording of participants’ performance using screen recording software such as Techsmith Camtasia™.

The third class of knowledge elicitation methods examines the structure of domains and concepts. Conceptual techniques are indirect and generate graphical representations of the structure of a domain, the relationships between the concepts in that domain, and the strength of those associations. Cognitive mapping and multidimensional scaling are examples methods in this category. Conceptual graph analysis attempts to capture declarative
knowledge elements (e.g., facts and rules) about a subject area from participants (Gordon, Schmierer, & Gill, 1993).

Each branch of knowledge elicitation methods has both strengths and weaknesses, making certain sets of techniques better suited to extract certain types of information better than others. Hoffman (1992) first proposed the *Differential Access Hypothesis* which states that different knowledge elicitation techniques will tap into different kinds of knowledge with greater or lesser efficacy. According to Cheatham, Converse, Barlow, and Kahler (2000) the Differential Access Hypothesis pertains to the sensitivity that a knowledge elicitation method has toward the acquisition of declarative knowledge and procedural knowledge, some techniques are more responsive to one type of knowledge as opposed to the other. They investigated the degree to which working memory characteristics influenced the adequacy of certain techniques (e.g., card sorting and conceptual graph analysis). Cheatham and her colleagues advised that knowledge elicitation methods should be selected relative to the type of working memory (e.g., iconic or echoic) that is stimulated by a task (Cheatham, Converse, Barlow, & Kahler, 2000). Process tracing methods are good for extracting procedural knowledge whereas conceptual methods are best for declarative knowledge. For example, protocol analysis (a process tracing method) does not work well when used for classifying information. Hoffman later retracted his support of the Differential Access Hypothesis – he contended that it was flawed in that no strong evidence had ever been produced to support it because, irregardless of their nature, all knowledge elicitation methods “can say things about so-called declarative knowledge, so-called procedural knowledge, and so forth” (Hoffman & Lintern, 2006, p. 215). He went on to propose *Differential Utility*, a postulate asserting that
any given knowledge elicitation technique can be more applicable to certain domains. Shadbolt and Burton (1989) suggested that instead of using one technique in isolation, several complimentary techniques should be used such that they all converge on the knowledge that one is attempting to elicit.

Cognitive task analysis (CTA) evolved from task analysis and combines task analytic techniques with methods of knowledge elicitation in order to derive an understanding of the cognitive activities and the knowledge underlying one’s performance of a task or series of tasks (Bonaceto & Burns, 2007). Task analysis, the precursor to CTA, aimed to examine behavior and task performance in the context of work environments where human to human interactions and human to machine interactions occur and then describe and analyze this information with the intent of rectifying performance and environmental issues that are detrimental to the execution of a task. A properly conducted task analysis results in a description and visual representation of the task and its ancillary components, and if a particular scenario deems it necessary a simulation of the task can be produced from the task analysis data and subsequently tested by participants (Kirwan & Ainsworth, 1992).

According to Kirwan and Ainsworth (1992), task analysis begins with data collection and they describe several methods for doing so: activity sampling, observation, questionnaires, and structured interviews. Activity sampling looks at the relative frequency of task behaviors and involves examining the amount of time a participant spends on the components of an activity and sampling behaviors at regular intervals (e.g., every 15 minutes or every hour) or predetermined times. With activity sampling, data is collected via a simple tally, recording the number of times a behavior or activity is observed, or a by sequential sampling, which
records the number of times and the sequence in which a task is performed. Observation is more qualitative in nature, non-obtrusive, and involves an in-depth description of the work environment, participants, and the tasks that are performed. Observation is best implemented when the activity under study is recorded using video. Questionnaires possess a high degree of specificity regarding the task being investigated because of the responses that can be elicited by the instrument. Questions can be presented in various forms (e.g., multiple-choice, open-ended, rating scales, ranking). Structured interviews, similar to the type of interviews used for knowledge elicitation, facilitate the systematic collection of task related information and can be conducted at either the beginning or the end of a task analysis.

Once the task analysis has been conducted, a description and representation of the activity is produced. Diaper (2004) demonstrated how an activity list is composed and arranged using video recordings of air traffic controllers at a United Kingdom airport. He recommended that recording(s) of an activity should be iteratively watched, with the researcher identifying “the actions and other things with their times” (p. 40). From this, a chart called an activity list can be made. An activity list includes an identification number for each action, each action’s time, a description of each action, and the researcher’s comments. Flow charts, link analysis, and timeline analysis are concise and succinct methods used to describe, represent, and draw inferences from a task analysis (Kirwan & Ainsworth, 2002). Flow charts delineate how an activity proceeds from beginning to end (step-by-step) as well as the transitions between steps—process charts, input-output diagrams, and decision action diagrams are examples of flow charts. A link analysis identifies the relationships (i.e., links) that exist between individuals and the parts of a system during the execution of a task, and
represents this information in the form of a link diagram where individuals and system elements are portrayed as circles and boxes and links are lines between them. Timeline analysis looks at the temporal relationships between task elements and the amount of time needed to complete a task. According to Kirwan and Ainsworth (1992) timelines, bars whose lengths are proportional to the amount of time dedicated to each task element, are arranged in succession in a graph that displays time along the x-axis and lists the subtasks (i.e., task elements) along the y-axis. They suggested that a timeline analysis can adequately help a researcher to determine what needs to be done to complete a task and how long these activities take within the context of the whole task. After a task’s description and representation are examined one is at liberty to draw inferences about the task and then its performance may be altered and enhanced.

The form that a task analysis takes is dependent upon the research being conducted. Hierarchical task analysis (HTA) builds upon traditional task analytic methods and is designed to decompose a task into its primary goals and sub-goals, and produce a hierarchy of these task elements. HTA seeks to “relate what operators do (or are recommended to do) and why they do it and the consequences if it is not done correctly” and the technique is useful for identifying and preempting current and future performance failures (Annett, 2004, p. 75). The results of a HTA can be represented in a hierarchical diagram that sequentially presents the operations, goals, sub-goals, and plans (i.e., the conditions under which sub-goals are carried out) of a complex task. If procedural knowledge is a salient characteristic of a task then the Goals, Operators, Methods, and Selection rules (GOMS) method can be employed. Operators are the steps that a user performs, methods are composed of operators
and facilitate the accomplishment of goals, and selection rules are discriminatory meaning that they “choose the appropriate Method depending on the context” (Kieras, 2004, p. 84). This procedure begins with a basic task analysis that allows a researcher to describe how individuals can accomplish goals within a systems environment and then a GOMS model of the task is constructed. A GOMS model uses formal notation and can be simulated using software that understands GOMSL, a programming language that executes GOMS models.

Task analysis possesses a limitation—it is superficial in the sense that it only examines the procedural aspects of task execution, it does not examine the cognitive aspects of task performance. A more elaborate methodology such as Cognitive Task Analysis (CTA) is required if one wishes to understand what internal representations (i.e., mental models) underlie the decisions and actions of a task. CTA evolved from task analysis during the 1970s during an era where the subfield of cognitive psychology rose to prominence in psychological research as psychologists and learning scientists began to place more emphasis on the cognitive aspects of learning and task performance (Annett, 2000). The goal of CTA is to “uncover the cognitive activities that are required for task performance in a domain to identify opportunities to improve performance through support of these cognitive activities” (Potter, Roth, Woods, & Elm, 2000, p. 317) and a CTA is applicable to the study of tasks that utilize cognitive skills. As researchers attempt to identify and accommodate the training needs present in a task environment (e.g., human-computer interaction, systems, and work environments) a CTA can be used to identify where leverage points exist and how they can be adapted in order to enhance performance. Hoffman and Lintern (2006) characterized a leverage point as an element or factor of the task environment that can be modified and
infused with technology that supports task performance. The identification of leverage points subsequently informs the creation, simulation, and application of tools designed to increase the accuracy and efficiency of task execution.

A CTA begins with bootstrapping, the process in which the researcher becomes familiar with the task under investigation and its corresponding subject matter. Bootstrapping is done by reviewing the documentation (e.g., technical manuals, reports) within a field and consulting with subject matter experts (SMEs). The goal of this initial step in the CTA is to identify the nature and structure of the knowledge used during task performance and it is through this process that the researcher gains familiarity the nomenclature, knowledge base, and procedures of the task (Chipman, Schraagen, & Shalin, 2000). Next, knowledge elicitation occurs in the form of observations, interviews, self-reports or narratives about task performance, and verbal protocols. During this portion of a CTA several complimentary and converging knowledge elicitation methods can be employed to extract information about cognition and the execution of the task. Crandall, Klein, and Hoffman (2006) recommended a novel approach to CTA that functions by utilizing experiment-like tasks and collecting data on participants’ performance. They suggested that these tasks come in two varieties: constrained processing (CP) tasks and limited information (LI) tasks. CP tasks are ones that are familiar to participants but the tasks have been altered or constrained in some form or fashion such as requiring the participants adapt a particular strategy to execute the task or by providing interference to the normal strategy or routine employed during performance of the task. LI tasks are problem-like in the sense that they only provide participants with incomplete information regarding a task and the participant has to complete the task on the
basis of this information. After knowledge elicitation and acquisition has taken place the data, which can be both qualitative and quantitative in nature, is examined and structured so that inferences about the underlying cognitive skills of task can be made. Lastly, the information, knowledge, and inferences contained within the data are represented via methods similar to ones described in the preceding paragraphs about traditional task analysis (c.f., Crandall, Klein, & Hoffman, 2006).

Hutchins, Pirolli, and Card (2007) described a two part study in which they used a CTA to analyze the activities of Naval intelligence analysts. The goals of the study included identifying leverage points where the performance of the intelligence analysts’ jobs could be improved and establishing standards for the design and development of analytic technologies. The first part of the study consisted of bootstrapping – Hutchins and his colleagues attempted to learn about the analysts’ \( n=6 \) daily activities and the cognitive challenges that they faced when assimilating information and making decisions based upon that information. This bootstrapping enabled the researchers to develop Critical Decision Method (CDM) probes for the second part of the study. The CDM is a storytelling technique that inquires about critical incidents experienced by a participant in a specific domain and CDM yields a narrative account of the incident and what was done to resolve it (Seamster, Redding, & Kaempf, 2000). Part two of the study involved CDM interviews where a set of National Security Affairs (NSA) intelligence analysts \( n=4 \) were required to recall a strategic analysis problem that they had previously encountered and then delineate step-by-step how they solved the problem. Hutchins and his colleagues produced cognitive demands tables in order to identify the cognitive challenges faced by intelligence analysts. These tables categorized the
challenges by task and outlined the cues, strategies, and potential errors associated with each challenge. The information derived from the second part of the study was then used to initiate the development of intelligence analysis technologies. This study demonstrates how a CTA is undertaken and how its workflow progresses from bootstrapping to knowledge elicitation to data representation.

Current approaches to CTA encompasses a diverse array of methodologies focused on obtaining and representing cognitive strategies and skills, and two prominent techniques include Cognitively Oriented Task Analysis (COTA) and the Precursor, Action, Result, Interpretation (PARI) method (Shute, Torreano, & Willis, 2000). COTA concentrates on applying CTA to the knowledge that is crucial for job performance and expertise, and its four distinguishing characteristics are: 1) its emphasis on not only describing cognitive skills but job knowledge, 2) it focuses on a whole job, 3) COTA requires researchers to observe job performance in natural settings, and 4) COTA utilizes the representative sampling of job tasks. COTA has three stages: planning, job expertise description, and the development of the COTA product. The planning stage involves consultation between the researcher(s) and the SMEs on the job, usually between three and five SMEs are required. The SME consultation results in a task list for the job. Describing the job expertise (i.e., the second stage) is where the job is observed, knowledge elicitation occurs, and the job is decomposed into sub-goals and methods for completing the job. The development of the COTA product generally includes the production of test content and instructional design principles for training an individual to fulfill the job role. PARI consists of structured interviews that seek to elicit intricate knowledge about problem solving (Seamster, Redding, & Kaempf, 2000). For the
PARI procedure two SMEs are needed, one to design a problem and another SME to solve the problem. The first SME serves as the problem designer and produces the problem, problem statement, and the documentation associated with the problem. The researcher then observes the problem designer solve the problem and conducts an interview with the designer regarding the problem solving process. Lastly, the second SME (i.e., the problem solver) solves the problem in the presence of the researcher and problem designer. The PARI method allows a researcher to examine the expertise and all of the actions involved in the problem solving process in a cognitive context because SMEs are better able to articulate their intricate understanding of the nuances of the problem and the domain than novices.

**Summary**

Although internal representations can take three forms, depending on the information contained within them, the construct of mental models have more robustness and contribute more information towards comprehension and individual and team task performance than propositional representations and mental images. In order to instantiate and extract a mental model, knowledge elicitation methods are used and these techniques fall into three broad categories: observations and interviews, process tracing, and conceptual techniques. This categorization, proposed by Cooke (1994), coincides with the evolution of Differential Utility, which considers the ability of a given knowledge elicitation method to be more responsive to certain domains as opposed to specific kinds of knowledge which was the premise of the Differential Access Hypothesis. Hoffman and colleagues (2002) presented a similar assertion about the relationship between knowledge elicitation and domains when they compared the strengths, weaknesses, and overhead associated with several knowledge
elicitation methods (e.g., critical decision method, protocol analysis, and concept mapping) albeit they framed their assertion in the context of the Differential Access Hypothesis.

Despite the fact that HTA and GOMS can decompose a task into its constituent components (e.g., goals, sub-goals, methods, procedures, etc.), task analysis has a peripheral nature and most task analytic procedures only seek to describe the surface characteristics of performance and go no further in examining an activity. CTA developed as result of the drawbacks of task analysis. It attempts to describe the cognitive processes associated with tasks in a domain and does this by utilizing converging knowledge elicitation techniques to derive the mental models used for task performance (Hoffman & Militello, 2009). Although it has been practiced in various fields and activities, the literature records no direct efforts to apply CTA to the study of CAD education, though Christiaans and Dorst (1992) and Wiebe (2003) have attempted to use knowledge elicitation techniques in the form of concurrent verbal protocols to derive mental models from learners about their design process and CAD performance, respectively. Christiaans and Dorst (1992) used concurrent verbal protocol analysis along with the analysis of concept sketches produced by sophomore and senior industrial design engineering student to gain an understanding of the mental models used during the design process whereas Wiebe (2003) examined the mental models produced by CAD trainees who were transitioning between constraint-based solid modeling software packages. Both studies demonstrate that knowledge elicitation is applicable to understanding the design process and CAD, yet neither investigation elaborated on the cognitive processes underlying CAD performance or its effects—this may necessitate the use of CTA. In the next
section, the content and context(s) that inform the creation of internal representations will be examined.

**Learning from Multimedia**

Although mental models are internal representations, they are formed on the basis of information obtained from sources exterior to the individual – these sources are called external representations. According to Ertl, Kopp, and Mandl (2008) an external representation is a knowledge structure “displayed by physical symbols, objects or dimensions” (p. 1599) and can contain textual and graphical information. Words, images, graphs, and sounds are considered external representations. When different types of external representations are combined in order to present information for the purposes of entertainment or instruction, a multimedia message has been created (Mayer, 2008). A multimedia message (referred to as multimedia hereafter) is a communication of information consisting of external representations, words (presented textually or aurally) and images, that is intended to facilitate learning – it is within this context that external representations function as instructional elements that direct learners’ attention to the relevant aspects of learning tasks and activities. Of the many researchers that have offered recommendations about the use of multimedia, Tufte’s and Mayer’s guidelines have been the most robust with regard to the efficient design and presentation of multimedia for the purpose of instruction. Tufte (1990, 1997) advocated the succinct presentation in multimedia messages and offered various guidelines for enhancing the appearance and comprehension of multimedia presentations of complex information. For example, he suggested that charts, graphs, and
other displays of quantitative information should be devoid of “chartjunk” (i.e., flamboyant
decoration and extraneous details) so that the meaning of the data can be accurately
portrayed. Tufte (2006) also proposed the use of “sparklines,” small high-resolution
information graphics containing multivariate data, for efficiently characterizing events and
phenomena with sequential binary outcomes (e.g., medical research).

Both Tufte and Mayer, along with several other individuals, have proposed heuristics
for the use multimedia but Tufte’s recommendations only pertain to static types of
multimedia whereas Mayer’s guidelines encompass all forms of multimedia including
animation. Animation, a dynamic form of multimedia, is defined as “simulated motion
depicting movement of drawn (or simulated) objects” (Mayer & Moreno, 2002, p. 88). Lowe
(2008) suggested that animation enhances instruction because it enables learners to make
inferences and draw conclusions about dynamic phenomena and situations that would
otherwise be very challenging to observe and understand. During multimedia learning the use
of animation can contribute additional explanatory power to the subject matter under
consideration – the portrayal of the temporal progressions of a cycle (e.g., weather), spatial-
temporal information (e.g., ordered sequences), and visuospatial information all benefit from
the elucidative capabilities of animation (Hidrio & Jamet, 2008). Animation is not without its
fallacies; in particular, it is capable of imposing limitations on learning under certain
conditions. When the content presented via animation is innately complex and difficult to
understand, and when learners lack the necessary prior knowledge to make sense of the
content animation is ineffective and this leads to inefficiencies in learning (Tyversky,
Mayer (2008a) characterized these inefficiencies as effects of multimedia and categorized the ways in which to alleviate these effects as principles.

The **multimedia principle** is a fundamental tenet of Mayer’s conceptualization of multimedia learning. This key principle states that individuals learn more comprehensively from animation and narration together than from narration alone or other forms of multimedia such as static images and text (Mayer, 2008a). This principle applies more to novice learners than it does to advanced learners because advanced learners are better able to create mental models of the content under study due to the prior knowledge that they possess, whereas novice learners need to be able to establish an association between the verbal aspects of the content and the animation in order to engage in learning (Clark & Mayer, 2008). The ways in which multimedia is interpreted and informs learning will be discussed later. Other principles include the **coherence principle**, **modality principle**, **personalization principle**, **pretraining principle**, **redundancy principle**, **segmenting principle**, **signaling principle**, **spatial contiguity principle**, and **temporal contiguity principle**. These principles can be structured into three categories: 1) principles that lead to a reduction of extraneous cognitive load (i.e., mental workload unassociated with the objectives of the content under study), 2) principles that attempt to offset the amount of cognitive load directed at understanding innately complex and difficult material, and 3) principles aimed at facilitating the creation of robust mental models of the content in multimedia presentation (Mayer, 2008b). The first category is referred as **reducing extraneous overload**, the second as **managing essential overload**, and the third as **fostering generative processing**. Of the preceding principles the ones most critical to this study are the **coherence principle**, **personalization principle**,
pretraining principle, and segmenting principle. The coherence principle is part of the reducing extraneous overload category and suggests that learning occurs more efficiently when distracting details (e.g., irrelevant stories, graphics, sounds, and text) are removed from multimedia. Applying this principle increases the likelihood that learners will be concerned with aspects of instruction that are pertinent to the learning task. Both the pretraining principle and segmenting principle belong to the managing essential overload category, and are principles that attempt to offset the cognitive load associated with the complexity of the content. The pretraining principle bears upon learners’ prior knowledge because it recommends that the key concepts of the content should be presented “prior to presenting the processes or procedures related to those concepts” (Clark & Mayer, 2008, p. 438) whereas the segmenting principle considers how multimedia can be broken up into consumable portions, such that the complexity of the content does not overwhelm learners. The fostering generative processing category contains a set of principles aimed at facilitating the creation of mental models from multimedia by embedding social conventions into the presentation. The personalization principle advises that effective learning occurs when the narration in multimedia is delivered in a conversational style with intonation as opposed to a formal style that is less dynamic. Implementing this principle results in the narration having social presence where a learner is better able to become immersed in and understand the content.

Even though the application of the preceding principles can increase the efficacy of multimedia learning, it is necessary to understand the ways in which multimedia can be interpreted and acted upon. Mayer (1993) admonished researchers that the cognitive effects of multimedia need to be considered from a substantive standpoint and a multimedia learning
theory has to be established. There are two frameworks or theories that postulate and elaborate upon how external representations in the form of multimedia inform the creation of internal representations (i.e., mental models) – the Cognitive Theory of Multimedia Learning (CTML) and the Integrated Model of Text. Mayer’s CTML is based on three assumptions about cognition and multimedia learning: 1) information processing occurs in dual channels, 2) working memory has a limited capacity, and 3) meaningful learning occurs when individuals engage in the appropriate cognitive processing of information (Mayer, 2005). The first assumption considers that multimedia information generally takes two forms, visual information (e.g., static images or animation) and verbal information (e.g., aural or textual), and that working memory has both a visual channel and a verbal channel to process both types of information respectively. Although working memory has channels to accommodate visual and verbal material, the second assumption suggests that working memory has a restricted capacity to attend to and deal with information at any given time (please see the Cognitive Load Theory section for an explanation of working memory). According to this last assumption, the employment of certain cognitive process during learning leads to the creation of mental models of the content – this assumption is central to CTML because it underlies how the theory functions.

CTML proposes that multimedia learning takes place as a result of three operations: selection, organization, and integration (Mayer, 2008a). Upon exposure to a multimedia presentation, a learner engages in selection where they pay attention to the text and images that are relevant to the content. During organization this information is then assimilated in working memory, connections are formed between the information elements acquired during
the selection operation, and two internal representations are constructed, a pictorial model and a verbal model. The pictorial model is a knowledge representation of the selected images retrieved from the multimedia message whereas the verbal model is a representation of the selected text and sounds (e.g., spoken words). *Integration*, the final operation, is where both the pictorial model and verbal model coalesce to form a robust mental model of the content contained within the multimedia presentation. This process is guided by the learner’s prior knowledge, which determines what information remains in the mental model and what connections exist between the pictorial and verbal information now contained in the mental model. Although CTML does not explicitly delineate how integration occurs, Mayer (2009) pointed out that a cross channel capability exists in working memory by stating that “although information enters the human information system via one channel, learners may also be able to convert the representation for processing in the other channel” (p. 65). Schnotz (1993) directed attention to the ambiguity in CTML regarding integration – the theory lacks an adequate explanation of how the two qualitatively different types of representations (i.e., pictorial and verbal) can have cross-referential connections created between them when a mental model is produced. Schnotz’s (2002) Integrated Model of Text and Picture Comprehension addresses and elaborates upon his concerns.

The Integrated Model of Text and Picture Comprehension (IMTPC) considers that visual information and verbal information possess distinctive qualities and are represented differently in working memory, and the framework places emphasis on how those representations interact and are processed (Schnotz, 2005). Within the IMTPC, verbal information (e.g., text) serves as a *descriptive representation* consisting of “symbols that
have an arbitrary structure and that are associated with the content they represent simply by means of convention” (Schnotz, Bannert, & Seufert, 2002, p. 30) whereas visual information in the form of images are characterized as *depictive representations* as they resemble the content that they represent because of shared structural features (e.g., a photograph of the Statue of Liberty bears a strong resemblance to the actual Statue of Liberty). IMTPC is composed of two branches by which representations are processed and these branches ultimately unite and lead to the construction of schemata. The IMTPC is initialized when a learner is exposed to multimedia and the descriptive side of the Model delineates how descriptive representations are processed and the other side handles depictive representations. The descriptive segment of the model initiates with the viewing of the text component of a multimedia presentation, then semantic processing occurs (i.e., the underlying meaning of the text is extracted), and a propositional representation is produced. The depictive branch begins with the perception of an image and then structure-mapping takes place. Schnotz and Bannert (2003) introduced the structure-mapping hypothesis and it proposes that the structural features of an external representation (i.e., image) are mapped onto a mental model such that the form of a mental model is dictated by the structural characteristics of the image. The authors further elaborated upon this hypothesis by suggesting that the structure of a graphic can impact its associated mental model to the extent that the mental model can either support or interfere with subsequent task performance – they called these premises the structure support hypothesis and structure interference hypothesis, respectively (Schnotz, Picard, & Hron, 1993). As the branches of the model transform the content derived from the multimedia both the depictive and descriptive representations interact with each via model
construction and model inspection. Model construction involves the transition that a propositional representation takes to become a mental model, and model inspection is where content from the mental model informs the organization of a propositional representation, the execution of these two processes is the equivalent of integration in CTML. The production of a schema is the end result of the IMTPC because the propositional representation and mental model have been synthesized (Schnotz & Kürschner, 2008).

All of the frameworks discussed deal with multimedia and how it influences learning, with each having its own strengths and weaknesses. Tufte’s framework primarily discusses how to present multimedia messages and does not directly consider individual differences amongst learners, though Tufte does introduce the concept of information overload, which will be alluded to later in the Cognitive Load Theory section. Mayer, on the other, expands upon Tufte’s framework by considering how multimedia can inhibit and enhance learning depending on the way it is presented. He advocated for the use of several prescriptive principles that could guide and structure effective multimedia learning, proposing a theory that coincides with those principles. Mayer’s CTML assumes that text and image processing occur in parallel, whereas Schnotz’s IMTPC contends that no parallel construction exists between text and images because they are two different (and unequivalent) types of representations, a descriptive representation and a depictive representation respectively (Schnotz, 1993). Though all of the theories account for how the components of multimedia are reconciled in working memory as internal representations, none of them contemplates the role that interface interactivity plays in multimedia learning and performance.
Interactivity is defined as multi-directional communication (two-way communication at a minimum) between a learner and an instructional system (Mayer & Moreno, 2007). Interactivity allows learners to structure and adapt an information presentation (e.g., multimedia) to their individual cognitive needs and interactivity permits learners to optimize the information by “actively deciding about the ‘what’ and the ‘how’ of a given presentation” (Schwan & Riempp, 2004, p. 296). The mechanism that underlies interactivity is the modification of an external representation to promote learning. For example, when a learner pauses an animation they are engaging in interactivity because they are acting upon and modifying the animation by stopping its playback.

Mayer and Moreno (2007) suggested that five types of interactivity can exist within multimedia: dialoguing, controlling, manipulating, searching, and navigating. Dialoguing occurs when feedback is given to learners as a result of their action(s). Controlling and manipulating share the similarity of being able to directly handle and modify multimedia where controlling pertains to a learner determining the sequence and pace of the multimedia presentation, and manipulating refers to determining the resolution (e.g., zooming in or out) and setting the parameters that dictate how the multimedia will appear and be executed. Searching is indicative of initiating a query and seeking out new information, and navigating happens when a learner moves through the content areas (e.g., sections) of an information presentation.

Although interactivity can enhance multimedia instruction because learners can control how they view and react to multimedia, interactivity can also cause learners to experience disorientation and frustration (Wouters, Tabbers, & Paas, 2007). Bucy and Tao
(2007) called this the interactivity paradox, a phenomenon where interactivity can be beneficial or detrimental to learning depending on how it is incorporated into multimedia. They proposed the mediated moderation model of interactivity (referred to as the interactivity model hereafter) in which they suggest that interactivity can be modeled by considering the auxiliary factors that contribute to its influence on learners’ behavior. In the interactivity model interactivity causes media effects, behavioral (e.g., affective, cognitive, and physiological) responses to interactivity, and the pathway between interactivity and its media effects is interceded (or mediated) by learners’ perceived interactivity. Perceived interactivity is a “user’s perception of the interactive experience” and is indicative of the degree to which affordances and other media attributes with multimedia are utilized by learners (Bucy & Tao, 2007, p. 663). The relationships between interactivity, perceived interactivity, and the resulting media effects is subject to individual differences (e.g., prior knowledge, self-efficacy, cognitive ability, etc.) present within learners—for example, some individuals may have an affinity towards multimedia whereas others may be frustrated by it. These individual differences would result in different patterns of perceived interactivity and media effects, depending on the learner. The interactivity model demonstrates that interactivity consists of a confluence of factors that dictate its impact on multimedia usage and learning.

Summary

The respective research agendas of Tufte, Mayer, and Schnotz all attempt to explain how multimedia serves to enhance the presentation of information, but the frameworks proposed by Mayer and Schnotz also expound suppositions about the impact of multimedia on cognition. Both CTML and the IMTPC approach the ways in which multimedia contribute
to learners’ construction of mental models, but the IMTPC provides a more comprehensive consideration of the respective influences of visual and verbal information contained within a multimedia presentation on learners’ cognitive processes. Although Mayer’s interactivity principle states that individuals “understand a multimedia explanation better when they are able to control the order and pace of presentation” (Mayer, Dow, & Mayer, 2003, p. 810) because they act upon an external representation, the interactivity model takes into account the interactivity paradox and delineates the confounding elements associated with interactivity and how these factors can either enable or impede multimedia learning. Vekiri (2002) advised that for any type of multimedia (non-interactive or interactive) to be effective for learning, the limitations of working memory (i.e., short-term memory) must be addressed. If multimedia research deals with the visual and auditory information external to a learner then cognitive load theory deals with how this information affects one’s working memory capabilities and performance on tasks. In the next section cognitive load theory and its implications for learning will be presented.

**Cognitive Load Theory**

While the CTML and IMTPC frameworks for multimedia instruction discuss the cognitive processes underlying learning and allude to the influence that individual differences (e.g., cognitive ability, prior knowledge, and self-efficacy) have on subsequent task performance, these multimedia theories have yet to fully address the role that working memory plays in instruction. Cognitive load theory (CLT) concerns how hindrances to learning result from the limitations of working memory and the design of instructional
materials. The theory originated from two sources: Miller’s (1956) inquiry into working memory and Sweller’s (1988) research on problem solving. Working memory (WM) is where all conscious cognition takes place and it serves as the cognitive system that concurrently manipulates, maintains, and assimilates information on a temporary basis (Baddeley, 2002). WM consists of four structures that enable it to store and call forth information from long-term memory: the phonological loop, visuospatial sketchpad, episodic buffer, and central executive (Sternberg, 2009). Both the phonological loop and visuospatial sketchpad deal with information that is internal and external to the individual, the former facilitates the reception and integration of visual, spatial, haptic, and motor information whereas the latter concerns acoustic and verbal information. The episodic buffer is capable of temporarily maintaining information from the phonological loop and the visuospatial sketchpad, and the episodic buffer is the conduit through which information held in WM and knowledge from long-term memory are synthesized into a cohesive internal representation (e.g., mental model) that can guide action. The central executive guides attention (e.g., divide attention and switch attention) and is the force that coordinates the other WM structures. It has the capacity to allocate available cognitive resources toward the completion of a task. With WM possessing a transitory ability to hold moderate amounts of information in attention at any given time, it becomes necessary to quantify and determine the extent to which information can be retained and manipulated in WM.

Miller (1956) suggested that the amount of information held in WM could be expressed in bits and that due to the limited capacity of WM these related bits could be aggregated into chunks. Chunking organizes and groups bits into larger units of information
by recognizing the patterns of knowledge amongst and between bits and it is by this process that accuracy of WM is increased because the more disparate bits held WM, the more difficult it is for one to discriminate between pieces of information. Contemporary researchers have defined chunks synonymous with schemata and mental models (Kalyuga, 2009). Miller went on to propose that one could hold between five and nine chunks in WM at one time. Sweller’s (1988) research into the inadequacies of conventional problem solving methods (e.g., means-ends analysis) made a significant contribution to the development of CLT. He mentioned that problem solving “via means-ends analysis normally leads to problem-solution not schema acquisition…[and] conventional problems impose a heavy cognitive load which does not assist in learning” (p. 283). Sweller (1988) found that learners had to simultaneously hold too many interdependent problem states and goal states in WM when they employed means-ends analysis to complete problems, and combined with their lack of prior domain knowledge about the subject matter of the problems, they had little to no WM capacity remaining to dedicate towards learning or problem solving. While Miller’s and Sweller’s explorations into the capabilities of WM both indicate WM’s significance to cognition and learning, Sweller expanded upon Miller’s assertions about the amount of information that can be held and processed in WM at any given time by referring to the fact that these pieces of information interact with each other in ways detrimental to learning if not orchestrated by prior knowledge. These seminal postulates are fundamental to CLT.

CLT “attempts to explain psychological or behavioral phenomena resulting from instruction” (Moreno & Park, 2010, p. 9) and it is concerned with the mental load that surrounds and is imposed upon individuals during learning and task performance. Although
not discussed in much detail in the literature, the theory makes a distinction between mental
effort and mental load (i.e., cognitive load) – mental effort is the amount of cognitive effort
via working memory resources that is expended during learning and task performance, and
mental load is the psychological experience that arises from engaging in a task and it results
from individual differences and the complexity of the task (Moreno, 2010). There are three
types of cognitive load that can exist: intrinsic cognitive load (intrinsic CL), extraneous
cognitive load (extraneous CL), and germane cognitive load (germane CL).

Intrinsic CL is caused by the amount and nature of information that needs to be held
in WM during learning and performance as it pertains to the subject matter under study
(Schnotz & Kürschner, 2007). During learning several elements of information (e.g., bits or
chunks) pertaining to the content under consideration have to be held and maintained in WM,
and depending the nature of these elements (whether they are independent or dependent upon
each other to be understood) WM capacity can be solely dedicated to processing these
elements and consequently depleted. This phenomena is called element interactivity, it can
vary between two extremes (low and high), and it is governed by an individual’s prior
knowledge. Low element interactivity occurs when only a few elements need to be held in
WM and these elements are subsequently processed in succession whereas high interactivity
occurs when elements make reference to each other and “several elements must be
manipulated in working memory simultaneously” (Sweller, van Merriënboer, & Paas, 1998,
p. 260). Regarding element interactivity prior knowledge allows the elements to be organized
in ways such that WM functions efficiently because similar elements are aggregated into
chunks (i.e., schemata) and are treated as one element, which frees WM capacity. In this
way prior knowledge reduces intrinsic CL and according to Moreno and Park (2010) the only other way to reduce intrinsic CL is to reduce the number of interactive elements that have to be maintained in WM – this can be accomplished by segmenting content so that learners do not have to assimilate all of it at one time.

Extraneous CL is influenced by instructional design (i.e., the format of instruction). When the design of instructional materials induces unnecessary element interactivity—irrelevant to the subject matter but related to how the content is presented—then extraneous CL arises (Paas, Renkl, & Sweller, 2003). For example, placing irrelevant or superfluous graphics and sounds within a multimedia tutorial on algebraic equations can lead to increased levels of extraneous load because none of these embellishments concern the content being presented and they would inadvertently direct learners’ attention away from the focus of the presentation. Although Tufte (1990, 1997, 2006) only indirectly discussed extraneous CL from the standpoint of the incomprehensibility of information as a result of the presence of superfluous graphics, he did nevertheless articulate its effects on learning (e.g., chartjunk, data-ink ratio). Aside from misdirecting learners’ attention, the learners would then have to maintain and process the superfluous elements as well as the pertinent elements of the presentation in WM and it is likely that a high level of element interactivity would exist, which again would deplete WM capacity. Many times this type of cognitive load adversely affects learning because extraneous CL is being imposed simultaneously with intrinsic CL, leaving little WM remaining to dedicate toward learning (Mayer & Moreno, 2010). As the capacity of WM is fixed and cannot be exceeded, the amount of intrinsic CL and extraneous
CL imposed by a task (depending on element interactivity and instructional design) can deplete WM leaving no remaining capacity.

In scenarios where WM is not exhausted by the other forms of cognitive load, germane CL can be induced. Germane CL is cognitive load that is solely associated with learning, that is, cognitive load imposed by the formation of schemata. Kalyuga (2010) suggested that “the sources of germane cognitive load are auxiliary cognitive activities designed to enhance learning outcomes or increase levels of learner motivation” (p. 53). Knowledge elaboration, the process of using prior knowledge to expand and refine new information on a perpetual basis and assimilate it with information contained in long-term memory, underlies the construction and automation of schemata (Kalyuga, 2009). Once schemata have been constructed their likelihood of usage can be strengthened and schemata can be automated by constantly engaging in tasks that require their utilization. After a schema is automated, it no longer causes germane CL because it is does not require conscious maintenance and processing in WM. A synergy exists within the trilateral relationship between intrinsic CL, extraneous CL, and germane CL – free WM capacity can be dedicated to any of the three types of cognitive load and both intrinsic CL and extraneous CL can actuate germane CL, although intrinsic CL is a greater determinant for germane CL. Sweller (2010) was well aware of this insight and expressed an intuitive understanding of this relationship by recommending that instructional design should attempt to impose intrinsic CL, if any cognitive load at all, because the element interactivity that causes intrinsic CL can be reduced by the processes of schema acquisition, construction, and automation (i.e., WM is used to form connections between the interacting elements and to aggregate them into
schemata and then subsequently automate the schemata) which are the fundamental sources of germane CL.

The application of CLT to instruction produces phenomena called cognitive load effects (CL effects), resulting from manipulating the design of instruction in order to facilitate learning and performance. Essentially, a CL effect is an implication of using CLT to address the enhancement of learning and “most of the [CL] effects occur because a reduction in extraneous cognitive load permits an increase in working memory resources devoted to intrinsic cognitive load, [thereby] increasing germane cognitive load and enhancing learning” (Sweller, 2010, p. 44). Each type of cognitive load has CL effects associated with it, but the predominant CL effect that forms the foundation for the other effects is the *element interactivity effect* which pertains to intrinsic CL. According to this effect all the other CL effects can only occur in situations where high element interactivity (i.e., high intrinsic CL) is present. The other CL effects associated intrinsic CL are the *expertise reversal effect* and the *isolated/interacting elements effect*. Extraneous CL has several CL effects pertaining to it: the *modality effect*, the *redundancy effect*, and the *split-attention effect* (Chandler & Sweller, 1991). The *goal-free effect*, the *imagination effect*, the *variability effect*, and the *worked-example effect* are all associated with germane CL. The classification of these effects is not mutually exclusive meaning that CL effects such as the redundancy effect and the goal-free effect, which respectively concern extraneous CL and germane CL, also relate to intrinsic CL due to the fact that element interactivity resulting from the content under consideration (and not solely from instructional design) plays a substantial role in both effects (Moreno & Park, 2010). Although not discussed in this section, the expertise reversal
effect, the variability effect, and the worked-example effect will be considered in the context of instructional support in the *Scaffolding* section. CL effects designate how cognitive load responds to an instructional intervention but they do not function as a means to evaluate the amount of cognitive load experienced by learners making use of the instructional intervention.

Cognitive load can be quantified in several ways utilizing a variety of measures and instruments, and when cognitive load is combined with other variables associated with learning instructional conditions can be compared and the type of cognitive load imposed during different parts of the entire learning process can be *ascertained*. Cognitive load can be measured either objectively or subjectively with most of instruments being subjective (Brünken, Plass, & Leutner, 2003). The distinction between objectivity and subjectivity, as it pertains to the evaluation of cognitive load, is a matter of specificity regarding the task imposing the cognitive load. Objective measures attempt to adhere to a standard by which the cognitive load related to any task can be measured (e.g., heart-rate can be utilized as a measure of cognitive load in simulated flight tasks as well as arithmetic tasks). Brünken, Seufert, and Paas (2010) suggested that there are three kinds of objective variables corresponding to cognitive load: input variables, outcome variables, and process-related behavioral variables. Input variables include task complexity, which is “the amount of information that has to be extracted from the information source with respect to a specific learning goal” (p. 186) whereas outcome variables include learning and performance outcome measures such as accuracy and the number of errors made during the execution of a task. Neurological and physiological parameters such as metabolic activity (as depicted by
functional magnetic resonance imaging [fMRI]), pupil dilation, and eye movements serve as process-related behavioral variables (Clark & Clark, 2010; van Gog, Kester, Nievelstein, Giesbers, & Paas, 2009). Objective measures have the limitation of being global, that is, they provide a cumulative index of the cognitive load experienced by a participant and they suffer from multi-causality, this means that these measures do not allow the cognitive load to be decomposed into the factors that caused it and it is unclear which of these constituent causes were specifically addressed by experimental treatments (Brünken, Seufert, & Paas, 2010).

Subjective measures have considerably received more attention than objective measures and they are based on the premise that individuals are capable of providing an indication of the amount of cognitive load experienced or mental effort they have exerted during learning and task performance (Paas, Tuovinen, Tabbers, & van Gerven, 2003). Most subjective measures of cognitive load are systematic, as they permit the comparison of cognitive load associated with different tasks (i.e., cross task comparisons relative to cognitive load), as well as sensitive meaning that they enable the decomposition of the factors that caused the cognitive load in the first place (Hart, 2006). The majority of subjective measures commonly take the form of rating scales and the NASA Task Load Index (NASA-TLX) and Paas’ unidimensional 9-point Cognitive Load scale (9-point CL scale) are both common examples of subjective instruments used (Wiebe, Roberts, & Behrend, 2010).

The NASA-TLX originated from the consolidation and synthesis of several workload evaluation instruments, and it is a multidimensional scale consisting of six subscales that evaluate the determinants of a task’s cognitive load – the subscales also serve as
representations of these factors. The subscales are classified in three categories: 1) task-related scales, 2) behavior-related scales, and 3) subject-related scales. Task-related scales are subscales that correspond to the most common ways in which the demands of a task imposes cognitive load upon a person and these subscales include mental demand (MD), physical demand (PD), and temporal demand (TD). Performance (OP) and effort (EF) constitute behavior-related scales as they pertain to the exertion of effort to successfully complete a task, and Frustration (FR) attempts to consider the psychological effect of task demands on participants and it is the only subscale in the subject-related category. Each subscale is bipolar and ranges from one to 100 points having a rating step (i.e., interval) every five points. These subscales are necessary because individuals’ perceptions of what cognitive load is and the amount of it observed during learning and task completion tend to vary, and Hart and Staveland (1988) noted that “regardless of how individuals might personally define workload [i.e., cognitive load], workload is caused by different factors from one task to the next and subjects are sensitive to factors that are included in, as well as excluded from, the workload definition” (p. 169). This between-subject variability, individual differences in the amount of cognitive load experienced and reported by participants, makes it very difficult to make comparisons between participants’ cognitive load, but by utilizing the six subscales of the NASA-TLX it becomes possible to make a pronounced reduction in the between-subject variability and systematic bias of the instrument.

The NASA-TLX is an offline instrument meaning that it is only administered after a task is completed. After completing the task, participants evaluate the relative importance of each factor by engaging in 15 pairwise comparisons of the factors (i.e., subscales) in order to
determine which factor in each pair was the most significant source of cognitive load during the task. Next, participants then provide ratings on each of the six subscales. The results of the pairwise comparisons are then used to determine the weighting that needs to be applied to the rating scores. Weighting does two things: it provides an indication of participants’ inferences towards the factors that most contributed towards cognitive load and it helps to reduce between-subjects variability (Hart & Staveland, 1988). For example, if TD was selected three times as an influential factor (its weight) and it receives a rating of 30 on its respective subscale then it would have a subscale product of 90. An overall cognitive load score is calculated by subsequently weighting all of the subscales’ ratings, adding up all of the subscale products, and dividing the sum by 15 (the total amount of weight). Although other instruments, such as the Subjective Workload Assessment Technique (SWAT), make use of subscales, pairwise comparisons, and weighting they are not as sensitive as the NASA-TLX and are very cumbersome to administer (Rubio, Diaz, Martín, & Puente, 2004).

Paas’ (1992) developed an unobtrusive cognitive load scale, referred to as the 9-point CL scale, that can be used as an offline and online (i.e., it can be administered during learning and task performance) measure of the amount of mental effort one invests during learning and task completion. The 9-point CL scale is symmetrical and its poles are labeled as very, very low mental effort and very, very high mental effort with neither low nor high mental effort in the center of the scale. It is highly reliable having a Cronbach’s alpha of .90. Some researchers have adjusted the number intervals and the labeling of each interval contained within the original scale – for example, Marcus, Cooper, and Sweller (1996) used the scale to evaluate cognitive load in the form of task difficulty by reducing the scale to six
intervals and labeling the poles as very easy and very difficult with neither easy nor difficult in the center. For a review of studies employing the 9-point CL scale, see van Gog and Paas (2008).

Cognitive load measures are often supplemented by circumstantial data (e.g., test scores, number of errors, latency) from the context in which instruction and performance take place because “a meaningful interpretation of certain level of cognitive load can only be given in the context of its associated performance level and vice versa” (Paas, Tuovinen, Tabbers, & van Gerven, 2003, p. 67). Paas and van Merriënboer (1993) proposed the construct of instructional efficiency to consider and evaluate cognitive load in the purview of learning. It measures the efficacy of instructional strategies relative to the cognitive load imposed by them and it enables the comparison of these strategies. Instructional efficiency can vary between two extremes, high instructional efficiency and low instructional efficiency (Paas & van Merriënboer, 1993). High instructional efficiency occurs when performance is maximized and incurs a small amount of cognitive load whereas low instructional efficiency occurs when performance is low and the amount of cognitive load incurred is high. The baseline for instructional efficiency is an efficiency of zero where performance is equal to cognitive load.

Mathematically, instructional efficiency is a statistical transformation that uses standardized cognitive load scores as well as standardized test scores to calculate efficiency (see Table 2.1). \( R \) is the mean cognitive load score, \( P \) is mean performance (i.e., test score), and \( E \) is efficiency. This is known as the original two dimensional formula (original 2D formula) and the values for \( R \) pertain to the cognitive load imposed by the test from which \( P \)
is obtained (e.g., a cognitive measure is administered immediately after the test is completed). If the difference between R and P (e.g., R-P) is less than zero, then E is positive and instructional efficiency is high but if the difference is greater than zero then E is negative and instructional efficiency is low. The original 2D formula’s application goes as follows: 1) all of the cognitive load scores for an instructional condition are standardized and then the mean of these scores (R) is calculated, 2) all of the test scores for the same instructional condition are standardized and then the mean of these scores (P) is calculated, and 3) these values are inserted into the formula and efficiency is computed. The efficiency values for various instructional conditions can then be compared using inferential statistical tests (e.g., t-test, ANOVA, etc.).

Table 2.1. Efficiency Formulae

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<th>Original 2D Formula</th>
<th>Adapted 2D Formula</th>
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The original 2D formula has been extended into two other efficiency formulae, the adapted two dimensional formula (adapted 2D formula) and the three dimensional formula (3D formula) (Tuovinen & Paas, 2004). The adapted 2D formula measures learning efficiency, the efficacy of the learning during training, as opposed to instructional efficiency, which assesses the value of instructional interventions relative to testing (see Table 2.1). The cognitive load incurred during the learning phase of training is represented by \( E_L \) and \( P \) represents test score. Both variables are standardized and this formula shares the same
baseline (E=0) as the original 2D formula although the source of cognitive load is learning. When high test performance is achieved with low cognitive load during the learning process then high learning efficiency is attained but low learning efficiency is realized when the inverse scenario occurs. The 3D formula measures three dimensional instructional efficiency and is “a more representative indication of the overall instructional process than either the learning [adapted 2D formula] or test [original 2D formula] efficiency measures, because it incorporates in one measure the effort throughout the whole process, rather than only during one part of it” (Tuovinen & Paas, 2004, p. 149). It considers both the cognitive load imposed by learning and testing in conjunction with test scores, and while \( E_L \) and \( P \) remain the same from the adapted 2D formula, \( E_T \) (the cognitive load associated with testing) is now incorporated into the equation (see Table 2.1). The baseline, or neutral, 3D instructional efficiency is denoted by the following equation: \( E_L + E_T - P = 0 \). Similar to the extremes associated with the two preceding formulae, there exists high 3D efficiency and low 3D efficiency. The former occurs when concurrently there is high test performance and low cognitive load imposed during learning and testing, and the latter signifies low test performance and high cognitive during learning and testing.

Of the three efficiency formulae, the two that are most capable of providing information about the kinds of cognitive load levied upon learners are the original 2D formula and the adapted 2D formula. The efficiency associated with the original 2D formula is indicative of the effects of germane CL on learners because it stands to reason that if a learner has acquired, assimilated, and automated more schemata (i.e., gained more knowledge due to effective instruction) during learning, prior to taking a test, they will
experience a small amount of cognitive load during testing in contrast to learners who were not able to construct and elaborate enough schemata (i.e., gained less knowledge as a result of inadequate instruction) before taking the test (Paas & van Gog, 2006). Thus, high instructional efficiency implies that germane CL occurred during learning whereas low instructional efficiency implies that it did not. Learning efficiency, the efficiency corresponding to the adapted 2D formula, is indicative of the extraneous CL caused by instructional designs (van Gog & Paas, 2008). If an instructional condition has been designed to appropriately promote learning and deliver instruction then learners should experience a low amount of cognitive load during learning and they should subsequently have high test performance, but if instruction has been designed inadequately then learners should incur a high amount of cognitive during learning and have low test performance. Accordingly, high learning efficiency implies that a certain instructional design is more effective than another because it imposes less extraneous CL than an instructional design having low learning efficiency. van Gog and Paas (2008) provided apt comments about the utility of both formulae, they suggested that “the adapted measure seems most useful in situations where the aim is to reduce cognitive load during learning…[and] when instruction aims to stimulate learners to invest high levels of effort in processes relevant for learning...the adapted measure does not seem very suitable.” (p. 22). Making use of all three formulae could enable researchers to precisely diagnose and rectify instructional design issues.

**Summary**

CLT emerged from research on WM and problem solving. It is a learning theory concerned with the role WM plays in knowledge acquisition and learning, and how
instructional design and the limitations of WM can inhibit and enhance training and performance. The cognitive load levied upon learners can be instantiated in three forms and the trilateral relationship between intrinsic CL, extraneous CL, and germane CL is interactive with respect to WM. All three types of cognitive load consume WM resources (e.g., attention) and when any of them co-occur with each other two things can happen depending on their ratio or proportion of occurrence: 1) WM can be exhausted and cease to function efficiently or 2) effective learning can take place. As most CL effects are not mutually exclusive to one type of cognitive load either of the preceding scenarios can initiate one or more CL effects.

While several instruments evaluate the cognitive load incurred by learning and performance, these measures only produce global cognitive load scores that indicate the overall cognitive load experienced by learners. They lack specificity in determining which kinds of cognitive load were imposed upon individuals. Although Ayers (2006) observed that “it is notable that subjective measures have only been used to calculate total cognitive load, no individual measures of intrinsic, extraneous or germane cognitive loads have been reported” (p. 390), he demonstrated that it is possible to differentiate between the various types of cognitive load during experiments by controlling the underlying causes of each kind. For example, he conducted two experiments where eighth and ninth grade students were asked to solve simple algebraic problems and afterwards participants were then asked to indicate the amount of cognitive load they had experienced while solving each problem. For both experiments Ayers assessed intrinsic CL (i.e., element interactivity) by holding extraneous CL and germane CL constant – he excluded instructional materials from the
study, which neutralized any cognitive load associated with learning or instructional design, and only asked the participants to perform the mathematical tasks. All of the efficiency formulae serve as descriptive indicators of how instructional conditions promote particular forms of overall cognitive load. The original 2D formula and the adapted 2D formula are indicative of germane CL and extraneous CL, respectively, whereas the 3D formula considers the efficacy of the whole training and performance process.

Two studies have been conducted regarding the application of CLT to CAD education and both only approached the rudimentary aspects of CAD performance. Chandler and Sweller (1996) and Martin-Michiellot and Mendelson (2000) investigated how the split-attention effect pertained to instruction for software usage. Both studies focused on the design of CAD software manuals and the execution of very simple CAD tasks (e.g., sketching a line segment, identifying menu commands) relative to the instructions provided by the manuals. Neither study had participants perform any kind of solid modeling task or measured the cognitive load associated with these types of tasks, so the influence of cognitive load on solid modeling performance remains to be seen.

An alliance exists between CLT and scaffolding with respect to learning, both cognitive load and scaffolding are necessary to produce learning and neither can do so alone. Moreno (2010) alluded to the reinforcement that scaffolding can provide to CLT by noting that “CLT is unable to unequivocally predict the learning outcomes resulting from working under, within, or beyond the ZPD [zone of proximal development] and to explain why the same learner may fail to learn under two qualitatively different load conditions” (p. 138). The cognitive load experienced by individuals during training can contribute to learning and
scaffolding informs how this cognitive load can be manipulated and how instruction can be structured to provide learners with the appropriate amount of support and assistance such that learning can be maximized. Conversely, if the appropriate kind of cognitive load (e.g., germane CL) is not elicited by scaffolding, then one will be unable to engage in effective learning (van Merriënboer, Kester, & Paas, 2006). The next section discusses the origins of scaffolding and the ways in which it can be used to enhance learning.

**Scaffolding**

The concept of scaffolding was derived from Lev Vygotsky’s Cultural-Historical Theory of Psychological Development (cultural-historical theory) and it is a means of instructional support provided to learners so that they can overcome problem-solving difficulties. The cultural-historical theory is a learning theory predicated upon two activities: imitation and internalization (Gredler, 2005). Vygotsky asserted that children use cultural signs and symbols (i.e., cultural semiologies) as tools for psychological development and learning. Language, which consists of linguistic signs used in verbal communication, is one such tool that “enriches and stimulates thinking, and through it, the child’s mind is restructured, reconstructed” (Vygotsky, 1993, p. 205). The use of these tools by knowledgeable members of the child’s social environment are observed and subsequently imitated by the child and this process of imitation then effects change within the cognitive processes of the child during internalization. These changes are initially informed by imitation until the child attaches the appropriate meaning to signs, symbols, and actions that were imitated (i.e., semantic linking). As internalization progresses, an understanding of the
cultural semiology is established and what was imitated is given meaning such that cognition is adapted to interpret and execute these behaviors.

The cultural-historical theory translates imitation and internalization from the social environment to the educational environment and argues that learning occurs as a result of an individual’s experiences in the learning environment. Vygotsky (1997) believed that a learner’s experiences are composed of reactions consisting of the perception of, processing of, and response to stimuli in the educational environment, and that learning is an active process in which these experiences, being catalytic in nature, precipitate new reactions. He suggested that the zone of proximal development (ZPD) is the area in which learning takes place and he defined it as “the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or in collaboration with more capable peers” (Vygotsky, 1978, p. 86). The ZPD is a developmental space within a learner which houses both an individual’s range of competencies and learning potential for problem solving in a domain. Its boundaries, the lower level (i.e., the existing level of competence) and the upper level (i.e., achievable level of competence), coincide with “what the child [i.e., learner] at a given time can imitate” (Valsiner & Van der Veer, 1999, p. 14) and within these boundaries the optimal conditions for imitation and internalization exist. Berk and Winsler (2005) suggested that the ZPD is dynamic and sensitive to a learner’s characteristics (e.g., aptitude, intelligence) because the ZPD can have a narrow or wide width depending on the capabilities of a learner; a ZPD with a narrow width indicates that learning only requires a small amount of instructional guidance to be effective whereas a wide ZPD necessitates a greater amount of
instructional guidance (e.g., more imitation and internalization need to occur). As an individual progresses through the ZPD during learning and task execution, the individual transitions from dependency on instructional guidance to a high degree of autonomy. This progression is due to a shift in the situation definition, the learner’s understanding and representation of a problem and its components (e.g., operators and environment), where the situation definition initially held by the individual prior to learning is either altered or relinquished in favor of a more comprehensive one (Wertsch, 1999). Movement within the ZPD is multidirectional – they could progress or regress within the ZPD, meaning that the learner can either acquire or lose proficiency for a task (Tudge, 1990). The ZPD’s multidirectionality signifies that instruction can enhance as well as inhibit learning. When instruction is effective and learning takes place, a new ZPD gets created and the upper level of the previous ZPD becomes the lower level of the new ZPD (Blank & White, 1999). Based upon this perpetual process, Brown and Ferrara (1999) recommended that instruction always be aimed toward the upper level of the ZPD so that learners are able to maximally engage in experiences that structure and elaborate their ZPD.

Although Vygotsky’s ZPD set the precedent for interpreting a student’s capability to learn and generalize knowledge to similar yet novel tasks, other conceptualizations of learning potential have arisen (Griffin & Cole, 1999). Some formulations place emphasis on the development of the learner and the delivery and presentation of instruction whereas others prioritize students’ understanding. For example, Chaiklin (2003) differentiated between two forms of the ZPD, the objective ZPD and the subjective ZPD, and he suggested that the former reflected the what a learner’s capabilities should be relative to their age and
level of exposure to specific subject matter, and that the latter ZPD represented the “child’s current [present] state of development in relation to” the objective ZPD (p. 50). Norton and D’Ambrosio (2003) proposed the zone of potential construction (ZPC), which they consider to be the extent to which the comprehension of a concept and task is encapsulated within a learner’s internal representations (i.e., mental models). The communication between an instructor and a learner contributes to a student’s progression through the ZPC because the instructor attempts to adjust the learner’s mental model such that an understanding is achieved via the abstraction of actions and operations of the task.

Along with approaching the theoretical aspects of the ZPD several authors have attempted to capture, measure, and evaluate the ZPD using a variety of methods, some of which are novel applications of assessment techniques. Dynamic assessment (DA) is a technique originating from intelligence quotient (IQ) testing and expands upon the limitations of IQ testing in order to understand a student’s learning potential because, as Allal and Ducrey (2000) noted, “traditional IQ testing provides measures which reflect the child’s present developmental level and previous learning, but does not offer any information about the child’s learning potential, cognitive modifiability, or future development” (p. 139). DA is administered in a stratified manner where an instructional intervention is embedded within assessment (e.g., pretest-teach-posttest paradigm) and it utilizes two metrics to evaluate and predict learners’ capabilities, change in skill and change in learning rate (Grigorenko, 2009). Kalyuga and his colleagues (2005, 2006) also examined a technique that evaluates an individual’s ZPD in terms of the amount of expertise exhibited by the learner while engaged in a task. His method is called rapid cognitive diagnosis and it observes the fluidity of
schema acquisition and retrieval during problem solving by examining the immediate
“traces” of schemata that remain in working memory after learning takes place (Kalyuga,
2006). Rapid cognitive diagnosis functions by attempting “to find out, after presenting a
student with appropriate stimulus materials for a limited time, what the highest level of
schematic knowledge or chunks (if any) the person is capable of retrieving and applying to
the presented material” (Kalyuga, 2006, p. 4) and to date rapid cognitive diagnosis has only
used mathematics as the subject matter upon which the procedure is executed. Kalyuga and
Sweller (2005) utilized the technique to dynamically adapt algebra instruction in real time to
changing levels of proficiency of high school math students. In their study they employed the
procedure in the following manner: during an instructional session participants would be
iteratively presented with an algebra problem and then were required to produce the first
solution step toward solving the problem within the time span of 60 seconds, and afterwards
they were asked to provide a cognitive load score via the 9-point CL scale. The researchers
measured learning efficiency and used it as a threshold to determine whether a participant
could continue progressing through the instructional session or if the participant needed to be
provided with remediation. In essence, rapid cognitive diagnosis seeks to align instruction to
a learner’s ZPD. Although RA and rapid cognitive diagnosis both try to approximate the
ZPD by exploring learning potential, the former by assessing general cognitive ability and
the latter by examining schema acquisition and retrieval, all of the preceding methods are
subject to a temporal fallacy that prevent them from accurately estimating the ZPD –
according to Valsiner and Van der Veer (1999) measurement is impossible because the ZPD
“refers to the hidden processes of the present that may become explicated in reality only as
the present becomes the (nearest) past, while the (nearest) future becomes the present…any empirical research effort can take place only within the present” (p. 15). Thus, no means of accurately surmising the ZPD currently exists and learning scientists and educators are only able to make inferences regarding its range relative to a student.

Instructional guidance within a learner’s ZPD that is provided by a teacher, capable peer, or instructional tool (e.g., computer program) is called **scaffolding**. This term arose from the research of Wood, Bruner, and Ross (1976) on tutoring, problem solving, and skill acquisition. Scaffolding is the “process that enables a child or novice to solve a problem, carry out a task or achieve a goal which would be beyond his unassisted efforts” (Wood, Bruner, & Ross, 1976, p. 90) and it is dynamic external support that supplements instruction in the contexts of learning and task completion. Wood, Bruner, and Ross examined how a group of children, ranging from three to five years old in age, could effectively receive scaffolding from an instructor during the process of building a pyramid with wooden blocks. Wood and his colleagues noted that there were six fundamental features of scaffolding: recruitment, reduction in degrees of freedom, direction maintenance, marking critical features, frustration control, and demonstration. Four of these characteristics are universal to all types of scaffolding regardless of format – reduction in degrees of freedom refers to making the requirements of a task succinct and manageable such that the learner recognizes the progress that they are making towards task completion and whether their course of action is correct or incorrect; marking critical features and direction maintenance function in a synchronous fashion where instructional guidance directs learner’s attention to the relevant aspects of a task and enables them to remain focused only on the specific objectives of the
task, respectively; and demonstration involves modeling and the explication of a task’s solution such that a learner can understand, imitate, and generalize the solution process.

In addition to the six preceding characteristics Puntambekar and Hübscher (2005) suggested that scaffolding consists of the ongoing diagnosis of a learner’s current level of understanding such that the instructor consistently monitors the student’s capabilities as well as their progress towards task completion, calibrated support that is based upon the learner’s continually changing level of knowledge, and fading (i.e., the gradual removal of the scaffolding once the learner is capable of performing the task independently). These attributes of scaffolding enable it to be dynamic because it is an external process that synthesizes two fluctuating levels of knowledge with respect to learners, “the level of competence embodied in the student…and the level of competence embodied in the level scaffolding” (van Geert & Steenbeek, 2005, p. 118). This interaction serves as a mechanism that facilitates real time changes in a learner’s level of domain knowledge by considering changes in the learner’s proficiency and predicing changes in instructional guidance upon those changes in the learner. Optimal scaffolding distance, learning rate, and demand-adaptation rate are parameters that are integral to enacting scaffolding’s dynamism (van Geert & Steenbeek, 2005).

Optimal scaffolding distance is the distance between a learner’s current level of performance and the level of scaffolding that is capable of maximizing learning and the learning rate. This learning rate is the rate at which the student’s level of performance (e.g., accuracy and efficiency) improves and, in conjunction with the demand-adaptation rate, it governs the learner’s movement thorough the optimal scaffolding distance. The demand-
adaptation rate is an estimate of the amount of assistance that a learner requires to complete a task in relation to the amount of time necessary to finish the task.

Even though scaffolding possesses specific characteristics that contribute to its dynamic nature, it must be realized that any one instantiation of scaffolding can only address short-term changes in learning if not incorporated into a broader instructional regimen (e.g., 4C/ID Model) (Miller, 2005). There are two principal causes underlying this: 1) learning is an active process that is constantly influenced by individual differences and instruction, and 2) the form that the scaffolding takes determines the efficacy of the instructional guidance presented to learners. The latter cause is of primary interest to this study.

Generally, scaffolding can take two forms, soft and hard, depending on how it is administered. The distinction between soft scaffolding and hard scaffolding is based on articulation and delivery – soft scaffolding is just-in-time assistance provided by a teacher or expert to a learner within the context of a learning environment, it is composed of verbal interactions between the instructor and the student (e.g., coaching), whereas hard scaffolds are more tangible; they are “computer or paper-based cognitive tools” that direct learners’ attention relative to instructional content and guide their interactions with the content (Belland, Glazewski, & Richardson, 2008, p. 407). Cognitive apprenticeship is an example of hard scaffolding that uses computer-based learning environments to provide learners with responsive and adaptive guidance analogous to the attention that a learner engaged in an apprenticeship would receive by presenting expert processes and focusing on the development of cognitive skills (Collins, 2006). Belland, Glazewski, and Richardson (2008) cautions that neither form of scaffolding (i.e., soft and hard) is not intended to replace the
other but instead they should be used to complement and amplify each other in order to promote learning.

A qualitative fallacy exists regarding the relationship between scaffolding and the ZPD – many authors have misconstrued scaffolding as being the same as the ZPD. Both entities relate learning to the individual but they are distinct. The ZPD is a model of an individual’s learning potential in a domain and it is mainly influenced by the learner’s development and experience, whereas scaffolding is a process that provides instructional guidance to a learner when necessary (Blank & White, 1999). The primary distinction between the two is that the ZPD is internal with respect to the learner, while scaffolding is external. The ZPD can only be acted upon by the learner themselves but it is scaffolding that facilitates this as well as the learners progression through the ZPD (Valsiner & Van der Veer, 1999). As the ZPD simulates a learner’s advancement in problem solving ability, whatever scaffolding that is provided to students should accommodate the expansion and transfer of problem solving ability – worked examples are a type of hard scaffold that can effectively and efficiently perform this function.

A worked example is a prototype of expert problem solving processes. It models these processes and consists of a problem formulation, solution steps and strategies, and a final solution to the problem formulation (Renkl & Atkinson, 2010). Worked examples are also referred to as goal-free problems because they alleviate both intrinsic CL and extraneous CL as well as circumvent the hazards (e.g., intrinsic CL) of the common problem solving process of means-ends analysis. It does so by eliminating the need for learners to search for and maintain problem states, goal states, the differences between these respective states,
subgoals, and operators in WM as they simultaneously attempt to employ domain knowledge to solve a problem. Instead, worked examples focus students’ attention on the relevant problem states and solution procedures of a problem such that the intrinsic CL imposed by the problem is minimized to a such a degree that learners can experience germane CL while acquiring relevant domain knowledge (van Merriënboer, Kester, & Paas, 2006).

The worked example effect is derived from this phenomenon and it dictates that deeper learning and better problem solving performance occurs from example-based learning using goal-free problems (Renkl, 2005). Worked examples function by facilitating the acquisition, abstraction, and automation of schemata related to the structure and solution procedure(s) of a problem, and the broader categories of problems of which the problem under consideration is part of. In a series of five experiments comparing the benefits of example-based learning and conventional problem solving methods for algebraic transformations, Sweller and Cooper (1985) found that worked examples were substantially effective in enabling learners to construct robust schemata (e.g., better mental models of problems) and produce superior problem solving performance compared to participants that employed means-ends analysis during learning and problem solving. The authors concluded this because “the ease with which schemas can be acquired is inversely related to the amount of goal-directed problem-solving search required” (p. 61) and worked examples reduce the time it takes for schema acquisition to occurs, thus increasing the quality of schemata.

This superior performance possessed one inconsistency – it was only exhibited when the example-based learners were solving near transfer problems, while their performance was equal to that of the conventional problem solving participants when they attempted to solve
far transfer problems. In a subsequent study consisting of four experiments, Cooper and Sweller (1987) examined whether exposing participants to multiple worked examples on algebraic transformations could enable them to develop and generalize schemata such that superior performance could be achieved on far transfer problems. The results of their investigation indicated that providing learners with the opportunity to study multiple worked examples prior to problem solving or testing facilitated both superior near and far transfer performance on algebraic transformation and word problems when compared to learning using means-ends analysis. The quantity of worked examples during learning is not the only factor that contributes to far transfer performance; it is also the quality of the worked examples that influences transfer. If the worked examples presented to learners have differing surface features (e.g., cover stories) as well as differing structural features then the worked examples will permit learners to abstract their schemata to a higher degree than learners studying worked examples with similar surface and structural features. This is known as the variability effect (Sweller, 2010).

Paas and van Merriënboer (1994) observed the existence of the variability effect by exploring how varying levels of worked example variability (i.e., presenting a diverse array of worked examples at high and low levels of variability) would impact participants’ performance on far transfer geometry problems. They determined that incorporating a high level of variability into example-based learning was advantageous for problem solving performance on near transfer and far transfer problem because participants were able to compare worked examples against each other and make sense of the similarities and differences that were present between them. They also noted an interesting phenomenon
pertaining to their findings – while worked examples reduced the intrinsic CL and extraneous CL associated with learning and problem solving, the participants utilizing high variability worked examples reported experiencing a high level of cognitive load yet still exhibited superior near transfer and far transfer performance. This anomaly was indicative of one of the primary implications of employing worked example instruction, it imposes germane CL upon learners (Paas & van Gog, 2006).

All of the preceding studies demonstrate that worked examples cause germane CL and enable the effective development of schemata, and that the robustness of one’s schemata is essential to performance on both near and far transfer problems in a domain. In each one of the studies, worked examples were presented to learners in the early stages of instruction, with respect to each study’s subject matter, and it is evident that the exposure to multiple and variable worked examples during this period was beneficial.

Worked examples can also be designed in a variety of ways to promote learning. Process-oriented worked examples emphasize solution procedures and strategies as opposed to the final solution itself, while product-oriented worked examples provide equal attention to the givens, goal states and relevant relationships between those states, and the final solution (van Merriënboer, 1997). The use of these types of worked examples is dependent on the subject matter under consideration. The designs of molar worked examples and modular worked examples are adapted to either slightly or considerably minimize intrinsic CL by the way that the information contained within the worked example is organized and presented to learners. Most worked examples typically employ a molar design where the problem states, goal states, and solution strategies are the base level entities that receive emphasis. Although
the amount of information that interacts in and needs to be held in WM is reduced, a moderate amount of intrinsic CL related to the worked example remains present. A modular worked example, in contrast, “avoid references to cognitively demanding molar concepts like problem categories, clusters of structural task features, and…solution procedures are broken down into smaller meaningful groups of solution steps that can be understood in isolation” (Gerjets, Scheiter, & Catrambone, 2006, p. 107). This means that modular worked examples gradually increase the amount of information that students deal with over time such that a simple to complex or part to whole task relationship between the entities in the worked example is established and a learner’s growing domain knowledge is able to offset any increases in cognitive load as schemata are acquired and automated.

Gerjets, Scheiter, and Catrambone (2004) presented an example of the distinction between molar and modular worked examples by applying both designs to a probability word problem about determining the probability of which of seven sprinters would win a gold, silver, and bronze medal at an Olympic event. The molar worked example required that a problem solver to first recognize and identify the example’s task features (e.g., the problem was a permutation problem), determine the solution procedure (e.g., find the appropriate probability formula to use), apply the solution procedure, and then to determine the final solution to problem. The modular worked example asked that the problem-solver consider and calculate the probabilities of each sprinter as individual tasks and then aggregate those probabilities to ascertain the overall probability of determining medal winners. In a subsequent study comparing the use of molar worked examples with the use of modular worked examples, Gerjets, Scheiter, and Catrambone (2006) concluded that modular worked
examples enhanced learners’ performance on near and far transfer probability word
problems, whereas molar worked examples only enhanced near transfer performance.
Although the four types of worked example designs have the ability to promote learning and
effective problem solving practices, there has been no exploration of whether a mutually
exclusive relationship exists between the designs (e.g., can a process-oriented worked
example also be designed modularly?). What has been determined, though, is that intrinsic
CL can be manipulated via the design of worked examples and that particular designs are
better able to facilitate transfer performance.

Another central component of example-based learning is the ability of a worked
eexample to elicit inferences from learners about the worked example and the problem(s) to
which it applies. This ability, called example elaboration, consists of example processing
strategies (i.e., behaviors and techniques) “that prime the learner to draw inferences
concerning the structure of the example, the rationale underlying solution procedures, and the
goals accomplished by individual steps” (Moreno, 2006, p. 171). Without elaboration,
learners may not fully benefit from using the worked example. Stark, Mandl, Gruber, and
Renkl (2002) reported that example elaboration training during learning, where an expert
models how to use worked examples, is an effective way to instruct learners on how to
engage in example elaboration or example processing strategies. Stark and his associates
investigated the extent to which training dictated how participants engaged in example
elaboration while utilizing molar worked examples for accounting problems. They
discovered that learners that had received elaboration training were able to produce twice as
many inferences indicative of an understanding of the principles, goals, and operators of the
worked examples than a control group of learners that did not receive any elaboration training.

Other example elaboration methods include comparing multiple worked examples on the same subject matter and drawing inferences about their similarities and differences with respect to their structures and solution procedures (e.g., producing the variability effect). In a study exploring whether schema acquisition and development was better facilitated with instruction on rudimentary inferential statistics concepts requesting that participants either make within-category comparisons where they compared worked examples with similar structural features or that required the participants to make across-category comparisons where they studied worked examples with differing structural features, Scheiter, Gerjets, and Schuh (2004) concluded that across-category comparison was more beneficial for schema acquisition and allowed learners to effectively distinguish between varying statistics problems. Without the proper example elaboration training (e.g., instruction on how to compare examples), making within-category comparisons imposes a high level of cognitive load and is detrimental to problem solving performance.

Other example processing strategies require that feedback is either given to or produced by the learner during their use of worked examples. Hattie and Timperley (2007) defined feedback as the “information provided by an agent…regarding aspects of one’s performance or understanding” (p. 81) and acknowledged that the goal of feedback is to provide error correction and to reduce incongruence between a learner’s current level of understanding and performance and the desired or target level of performance dictated by instruction. Feedback is preceded by an individual’s action(s) during learning and task
performance, and it shares a temporal relationship with performance because the immediacy of feedback is determined by the goals of the instruction. For example, feedback about the accuracy and efficiency of task completion is best given immediately after the learner engages in the task, whereas feedback about the processes of task execution and the relationships that exist between task elements should be delayed so that the automatization of the processes underlying task performance are not interrupted (Hattie & Timperley, 2007).

Lhyle and Kulhavy (1987) conducted two experiments to determine how feedback impacted task performance, hypothesizing that “learners who are required to semantically analyze feedback following an instructional error should have a better chance of replacing the original error with the correct response on a later test” (p. 320). The first experiment contained a control condition that received no feedback and the remaining conditions received scrambled feedback and reiterated feedback, respectively; the second experiment contained a scrambled feedback condition, a condition where feedback was only given once, and a control condition. The results from the experiment one indicated that reiterated feedback condition exhibited the highest performance on a posttest and the results of the second experiment showed that feedback, in general, leads to higher performance. Lhyle and Kulhav ey (1987) concluded that the more time and effort that learners dedicate towards the semantic analysis of feedback (i.e., processing and studying the feedback), the better performance would be, remarking “lesson procedures that increase the amount of processing learners devote to feedback will also increase the effectiveness of the feedback itself” (p. 322). This suggests that meaningful feedback is central to learners gaining an understanding
of problems as well as proficiently solving them and it alludes to the fact that feedback has the potential to cause individuals to experience germane CL.

In the context of worked examples, feedback comes in two forms: instructional explanations and self-explanations. Each kind of feedback usually must be initiated by prompts: instructions that require learners to execute certain activities while engaged in example-based learning and embedded within the worked example (Horz, Winter, & Fries, 2009). For example, in a multimedia learning environment after reviewing a worked example, a learner may be asked to submit a response to a multiple choice question pertaining to a worked example’s solution step(s) and, upon the submitting the response the learning environment (i.e., computer program), may provide the learner with feedback regarding the accuracy of the response. An instructional explanation is feedback provided by a tutor or produced by and incorporated into instructional materials with the intent to improve learners’ understanding and performance (Sánchez, García-Rodicio, & Acuña, 2009). Self-explanation is an example processing strategy in which learners produce their own feedback to worked examples by generating inferences about the structure of the example in order to understand the problem solving procedures presented in it (Johnson & Mayer, 2010). Most worked examples, regardless of their design, contain abridged problem steps where two or more components of the solution procedure may be aggregated because it is assumed that the student has enough prior knowledge to ascertain the procedure (Chi & Bassok, 1989; Chi et al., 1989). In order for the worked example to be comprehended, its solution rationale must be apprehended by the learner; that is, the specification of why each solution step has to be
taken, what the conditions are that provoke each step, and the resulting consequences have to be understood (Wouters, Tabbers, & Paas, 2007).

Chi et al. (1989) researched the efficacy of self-explanations relative to physics word problems and found that participants that successfully studied worked examples tended to generate more self-explanations that included expositions about the structure of the worked examples as well as the domain principles and conditions that surround a solution step. These participants also recognized when they did not fully understand a concept or procedure presented in a worked example more often than participants that were less successful at using worked examples who, in contrast, failed to recognize that they did not understand concepts as often.

Atkinson, Renkl, and Merrill (2003) described two categories of self-explanation: anticipative reasoning and principle-based explaining. With anticipative reasoning one creates self-explanations by predicting the next solution step in a worked example and then verifying whether their prediction is correct. Principle-based explanations involve the articulation of the worked example’s structure as well as the underlying domain principles it is attempting to communicate. Anticipative reasoning explanations require a higher level of domain knowledge than principle-based explanations. Instructional explanations have the strength of presenting correct and coherent knowledge and information that enables learners to enhance their schemata, whereas self-explanations may not be accurate but still have the advantage of being individualized to a learner’s current level of understanding and performance. Hausmann and Vanlehn (2007) contended that more effective learning would occur if students generated self-explanations as opposed to being provided with instructional
explanations. In a study on physics worked examples, they discovered that the process of producing an explanation (i.e., self-explanation), and not so much the content of the explanation, was an important factor for example-based learning.

Both instructional explanations and self-explanations have the goal of helping individuals obtain an understanding of a worked example’s solution rationale. However, learners have the tendency to overlook instructional explanations and give self-explanations more consideration because self-explanations are generated by the learners themselves when they experience a comprehension failure. This is due in part because they are suited to learners’ individual levels of performance while instructional explanations are not (Sánchez, García-Rodicio, & Acuña, 2009).

Comprehension failures are also known as impasses, which occur when learners detect errors in their competency. Learners experiencing an impasse can receive benefit from either instructional explanations and self-explanations, depending on how each type of feedback is elicited. An impasse has to be encountered before either type of explanation is provided or produced, and learners have to realize that this has happened. Impasse triggers are cues that indicate that a learner has come across an impasse and that a misunderstanding may exist (Sánchez, García-Rodicio, & Acuña, 2009). A soft impasse trigger directs attention to small inaccuracies or fallacies in one’s understanding of a domain principle and strong impasse triggers provoke one to revise their overall mental model of an example. Prompts can function as impasse triggers because they “elicit high-quality self-explanations that are slightly out of reach for learners…and foster deep conceptual understanding” and are able to engage learners in active knowledge construction (Berthold, Eysink, & Renkl, 2009, p. 361).
Incomplete solution steps within a worked example also serve as impasse triggers because they can temporarily produce impasses that direct attention, placing emphasis on specific parts of the example as well as initiate self-explanations so that learners can ascertain the example’s solution rationale (Renkl, Atkinson, & Große, 2004). Although worked examples mitigate the limitations of means-ends analysis via their designed impasse triggers and produce example elaborations (and resulting increased germane CL), worked examples are not a panacea for learning because they can cause learning complications as a student’s domain knowledge increases.

Learner characteristics (e.g., aptitude, intelligence, etc.), or individual differences, dictate how effective worked examples are. One such individual difference that the learner brings to bear when engaging in example-based learning is the amount of prior domain knowledge (prior knowledge) that they have. Prior knowledge is “the learner’s content knowledge related to the domain studied, which is present before the implementation of a particular instruction” (Gurlitt & Renkl, 2010, p. 418) and it orchestrates the learning experience by structuring and aggregating novel information with the prior knowledge the learner already has. During the course of two experiments on the uses of worked examples for electrical circuitry instruction, Kalyuga, Chandler, Tuovinen, and Sweller (2001) observed that as participants’ prior knowledge increased, the participants studying worked examples exhibited a decreased level of problem solving performance on posttests whereas participants studying conventional problems requiring means-ends analysis demonstrated an increased level of performance on the same problems. The authors suggested that this outcome was caused by a relationship between a learner’s prior knowledge and instructional
design. This phenomenon is called the *expertise reversal effect* and, as Rittle-Johnson, Star, and Durkin (2009) noted, it also impacts example-processing strategies. They examined two groups of math students that either used worked examples that presented the same algebraic equation problem solved by two different methods or used worked examples that presented different algebraic equation problems solved by the same method in comparison to a control group that used sequentially presented worked examples. Rittle-Johnson, Star, and Durkin discovered that, in general, comparing worked examples is advantageous for learning how to solve problems, but learners with low prior knowledge benefit most from comparing worked examples that present different problem types using the same solution method or viewing sequentially presented worked examples. Learners with a high level of prior knowledge benefited most from comparing worked examples that present differing solution methods.

The expertise reversal effect is an aptitude treatment interaction (ATI) that transpires when instruction that is beneficial for learners with a low amount of prior knowledge is detrimental for learners with a high amount of prior knowledge, and vice versa (Schnotz, 2010). According to Cronbach (1975) an ATI is based on the individual differences of participants affecting their responses to treatment or instruction (its content and design). In the case of the expertise reversal effect, this reciprocal relationship is moderated by the domain knowledge learners have acquired prior to receiving instruction. The underlying mechanism of the expertise reversal effect primarily has to do with cognitive load and redundancy (i.e., superfluous information) – the expertise reversal effect is caused by the inappropriate cross-referencing of similar information provided by a learner’s schemata and instructional guidance (Kalyuga & Sweller, 2005). As one attempts to resolve the overlap between
equivalent pieces of information provided by two sources, one internal and the other external to the individual, certain information becomes redundant but must be maintained in WM until resolution is brought regarding the correspondences shared between the pieces of information. This causes a high amount of intrinsic CL and leaves no WM resources available to dedicate toward germane CL. Thus, learners with a lot of prior knowledge are likely to experience a high amount of intrinsic CL when using worked examples because they have to balance competing sources of information, whereas low prior knowledge learners will not because they would only be considering information from one source (i.e., the worked example), thus having WM resources available for germane CL. There is at least one way of counteracting the expertise reversal effect, but it requires altering the structure of worked examples.

Fading is the process of systematically restructuring a worked example such that one or more of its solution steps are omitted, facilitating the gradual removal of the instructional support that the worked example provides and directing learners’ efforts towards applying the knowledge that they have already acquired and thus engaging in independent problem solving (Moreno, Reisslein, & Ozogul, 2009). The following scenario illustrates how fading can be applied to a worked example: once a learner has studied several worked examples on a particular subject and their prior knowledge has been built up, he or she can then be presented with a worked example whose first or last solution step is either incomplete or excluded and the learner would be required to produce this solution step (i.e., solve the worked example). The learner is subsequently presented with worked examples that have
more and more solution steps missing until he or she finally has to solve a whole problem without any instructional guidance from a worked example.

Fading must not be applied in a cavalier fashion because, as Renkl and his associates found, the specific solutions steps that are removed are critical to the efficacy of fading. Renkl, Atkinson, and Große (2004) tested two hypotheses relevant to fading, the position hypothesis and the specificity hypothesis, and their effects on learners utilizing worked examples on probability principles. According to the position hypothesis, the position of the faded solution step(s) is most important and dictates learning; the specificity hypothesis contends that “learning outcomes are determined by the specific step that is faded” (p. 65). The results of the study rejected the position hypothesis and established support for the specificity hypothesis because participants learned the most information about the particular steps that were faded regardless of where the steps were located in the worked example. Renkl and his associates suggested that fading produces temporary impasses triggers within a worked example where the excluded solution step(s) exist, causing learners to engage in example elaboration activities such as self-explanation and ultimately leading to more comprehensive learning. Renkl, Atkinson, and Maier (2000) suggested that the errors learners produce during example study is a mediating factor between fading and problem solving performance, and that this mediation effect manifests itself in the influence fading has on near transfer and far transfer problem solving performance.

Fading can be arranged in two ways, forward fading and backwards fading. With forward fading solution steps in the beginning of a worked example are progressively omitted one by one until the learner have to completely solve the whole problem
independently and backwards fading functions in an opposite manner, where solution steps at the end of the worked example are sequentially faded. Forward fading imposes more cognitive load than backwards fading and has been found to only be effective for near transfer problem solving problem. In contrast, backwards fading is beneficial for both near transfer and far transfer problem solving and places a relatively low amount of cognitive load on learners as they transition from worked example study to independent problem solving (Atkinson & Renkl, 2007). Adaptive fading, a variation of backwards fading in which the solution steps of a worked example are faded at an individual learner’s rate of progress, has also begun to receive attention with several studies demonstrating its potential to improve problem solving performance (e.g., Moreno, Reisslein, & Delgoda, 2006; Salden, Aleven, Renkl, & Schwonke, 2009; Salden, Aleven, Schwonke, & Renkl, 2010).

Summary

Vygotsky’s cultural-historical theory suggests that learning occurs because of imitation and internalization, and the theory also establishes the ZPD as a construct that represents an individual’s learning potential and range of capability relative to problem solving and task performance. The ZPD is bounded by two limits – the lower limit, which coincides with the most challenging task that a learner can perform without any assistance from an instructor, and the upper limit, which coincides with the most difficult task the learner can perform with instructional guidance. The work of Bruner, Wood, and Ross (1976) is seminal to scaffolding, the process of providing instructional guidance to learners, as necessary. Although the work of Vygotsky as well as the work of Bruner and his colleagues approach the mechanisms by which learning occurs and how best to facilitate it, respectively,
it must be noted that the ZPD is not equivalent to scaffolding or vice versa. Instead the
following relationship between the two items exists: the ZPD is internal with respect to a
learner and it is only the learner that can manipulate it, and scaffolding is an external process
that enables the learner to progress through the ZPD. Schnotz and Kürschner (2007)
proposed that instruction (alongside scaffolding) directed towards tasks within an
individual’s ZPD are likely to promote germane CL because scaffolding can direct the
individual’s attention to the relevant aspects of the instruction which, in turn, reduces
intrinsic CL and leaves WM resources available to be dedicated towards germane CL.

Worked examples are hard scaffolds that assist with problem solving and mitigate the
cognitive load associated with means-ends analysis. They are also known as goal-free
problems because they focus learners’ attention on problem solving procedures and solution
steps without requiring the whole problem to be solved independently. Atkinson, Renkl,
Derry, and Wortham (2000) recommended that the intra-example and inter-example features
of worked examples should be given consideration prior to incorporating example-based
learning into an instructional regimen. Intra-example features are a worked example’s
characteristics pertaining its design and structure. Examples include how the solution steps
are presented, if the example is product-oriented or process-oriented, and whether it is molar
or modular. Inter-example features are “principally certain relationships among multiple
examples and practice problems within a lesson” (Atkinson, Derry, Renkl, & Wortham,
2000, p. 186) and have to do with how examples are sequenced within instruction. Ways in
which to employ inter-example features include presenting multiple worked examples that
have both variability in structure and cover story, and providing learners with example-
problem pairs where they first study a worked example and then solve a problem similar to the worked example that was studied. The individual differences of learners and ATIs, such as the expertise reversal effect, should also be considered prior to integrating worked examples into an instructional regimen. The transition from example-based learning to independent problem solving requires feedback in the form of self-explanations and fading, the consecutive omission of a worked example’s solution steps. Fading functions by creating temporary impasses that cause learners to engage in self-explanation regarding the step(s) that are excluded from a worked example. Backwards fading has been shown to enhance both near transfer and far transfer problem solving performance whereas forwards fading only improves performance on near transfer problems.

Previous research on the functionality and impact of worked examples has generally pertained to the domain of mathematics and a few other disciplines, and although it has only recently begun to be applied to the context of engineering education (Moreno, Reisslein, & Ozogul, 2009), no studies have explicitly addressed how to integrate worked examples into CAD education and subsequently evaluate their efficacy. This is what the current study will attempt to do. What follows is a synopsis of this chapter that delineates the relationships between each of the six themes that have been presented.

**Overall Summary**

From this review of the literature pertaining to the six content areas presented in this chapter, several theoretical and practical things become evident: 1) CAD training and education is in need of improvement with respect to solid modeling instruction, 2) internal
representations such as mental models are precursors to performance and expertise in areas such as CAD software usage, 3) an instructional regimen that incorporates worked examples and manages cognitive load may be beneficial for learning CAD and similar software tools, and 4) multimedia is an appropriate apparatus through which such an instructional regimen can be delivered. The efficiency of constraint-based solid modeling software usage is dependent upon the correct application of design intent, the sophistication embedded into an engineered part during the solid modeling process. For an engineer to accurately employ design intent he or she must have a robust internal representation (i.e., mental model) in order to predict its results and preempt any discrepancies that may occur during or following the application of a design strategy (Johnson-Laird, 1980; Rynne & Gaughran, 2007; Wiebe, 2003). As Piegl (2005) suggested, example-based learning may serve as a mechanism through which effective instruction on design intent can be provided because, although not heavily researched or evaluated in the context of CAD education, worked examples have the logical potential to enhance solid modeling instruction because they model expert problem solving processes and task performance (Renkl & Atkinson, 2010). In the case of design intent, they may be able provide a prototype of the correct ways of integrating it into the solid modeling process. If worked examples: 1) were to be placed within an instructional design framework, such as the 4C/ID model, 2) suited for a long-term training regimen that amplifies the development of the cognitive skills necessary to perform solid modeling tasks that utilize design intent, 3) that imposed a low to moderate amount of cognitive load during learning while accommodating the individual differences between learners, and 4) that promoted transfer (near and far) of these skills, then example-based learning may be
beneficial for CAD education (cf., van Merriënboer, 1997). As web-based learning has become prevalent in CAD education (Connolly and Maicher, 2005; Folkestad & de Miranda, 2001), multimedia has become the preferred apparatus through which any type of solid modeling instruction is delivered. When interactivity is integrated with multimedia, a dynamic form of learning (i.e., multimedia learning) is initiated that allows an individual to synthesize a good deal of essential and ancillary information at one time, and engage in deep learning.

Certain methodological considerations become apparent in light of exploring some of the theoretical and practical aspects of this literature review, specifically the appropriateness of specific techniques must be considered. Similar to most studies that assess instructional interventions, learning and performance outcomes must be evaluated not only to the extent that participants have acquired the knowledge and skills associated with the intervention, but also to the extent that they are able to generalize and apply the knowledge and skills to tasks that are similar and dissimilar to those presented in the instructional intervention – both near and far transfer of learning (Haskell, 2001). Other measures that are indicative of the effectiveness of an intervention must be utilized as well. The amount of cognitive load imposed by instruction in the forms of germane CL and extraneous CL can be examined via instructional efficiency and learning efficiency, respectively (van Gog & Paas, 2008). To fathom the impact of the intervention on task performance via an enhanced mental model, especially as it pertains to design intent, an apt technique such as CTA must be employed. As CTA offers a combination of converging knowledge elicitation techniques (e.g., retrospective verbal protocols, timeline analysis) and task types (e.g., constrained processing
tasks and limited information tasks), it is suited for deriving a glimpse of an individual’s mental model of design intent. Only a few of the methodologies discussed have been applied to solid modeling instruction and several theoretical aspects of the literature presented here have seldom been explored in CAD education in any form. In the following chapter the author proposes a research study that explores ways to enhance solid modeling instruction in the context of CAD education through an intervention that lends credence to the ideas present in this literature review.
Chapter 3: Methodology

The purpose of this study is to investigate how CAD curricula can be structured to effectively present the concept of design intent and promote instructional efficiency. Specifically, this study addresses the following research questions and their corresponding hypotheses:

1. Do interactive videos for SW tasks that incorporate worked examples and remediation alter participants’ instructional efficiency i.e., produce learning conditions conducive to high learning performance outcomes and low cognitive load?
   a. H1: Participants using interactive videos incorporating worked examples and remediation should experience higher instructional efficiency than those not exposed to the same materials.

2. Does using interactive videos for SW tasks that incorporate worked examples and remediation facilitate near and far transfer (i.e., the flexible translation and generalization of previously learned CAD skills to novel CAD tasks)?
   a. H2: Participants in both the treatment and control conditions should have relatively equal performance on near transfer tasks whereas participants exposed to the interactive tutorial videos should have higher performance on far transfer tasks.

3. Do the participants’ mental models reflect an understanding of design intent?
   a. H3: Participants who use the interactive videos should have more robust mental models of how to embed and apply design intent in SW.
Pilot Study

A pilot study was conducted to assess the proposed study design as well as the instruments of this investigation. The purpose of conducting a pilot study prior to the execution of a full-scale study is to “develop and try out data collection methods and other procedures” and preempt any discrepancies that may as a result from their usage (Gall, Gall, & Borg, p. 37). During the Fall 2009 semester, three sections of GC 120 with a total of 167 students participated in the pilot research. Each GC 120 section was randomly placed in one of three quasi-experimental conditions: Full Treatment (n=55), Partial Treatment (n=56), or Control (n=53). The majority of the pilot study’s participants were classified as sophomores and the other major constituency of the sample was juniors with only a few freshmen and seniors.

The pilot study utilized a *Nonequivalent Multiple Treatment and Controls with Pretest and Posttest Design*, where there were two treatment conditions and one control condition (Shadish, Cook, & Campbell, 2002) i.e., Dr. Wiebe’s section and one of Walter Kelly’s sections participated in the treatment conditions, respectively, and the remaining GC 120 section taught by Walter Kelly served as the control group (see Table 3.1). As each class served as the unit of analysis for the pilot study individual participants could not be randomly assigned to each condition because they were nested in one of the three GC 120 sections random assignment was used to place each section into the pilot study’s conditions (Shadish, Cook, & Campbell, 2002, p. 509). The GC 120 sections involved in the pilot study received access to tutorial videos through each section’s course website housed on NCSU’s LMS that incorporated demonstrations of how to create and interact with SW assemblies. The tutorial
videos were created using Adobe Captivate™ and Techsmith Camtasia Studio™, both software packages were used to screen record the SW demonstrations, and Adobe Presenter was used to create overviews for each tutorial video and corresponding SW assignment (i.e., advanced organizers of each SW demonstration’s and assignment’s objectives). The videos came in two forms, those that included fully worked examples (Full Videos) i.e., complete demonstrations of SW tasks and partially worked examples where the video only demonstrated a few steps of the SW task and the learners had to complete the remaining steps independently (Partial Videos). During the pilot study participants from all of the conditions were required to complete SW assembly exercises demonstrated in the tutorial videos that they had access to. These SW exercises included a far transfer assignment where learners had to generalize and apply knowledge from the tutorial videos to a SW assembly problem that was dissimilar to the content demonstrated in the videos. Participants were provided with each exercise’s associated SW files via each GC 120 section’s respective course website. The exercises included creating a clamp assembly, a c-bracket assembly, and a pivot assembly e.g., gear stick (far transfer SW exercise). The researcher also created a pretest and posttest by which to assess the learners’ knowledge on SW assemblies and related tasks prior to participating and after engaging in the pilot study. Both tests included five questions worth 10 points each that were delivered in various formats (e.g., true/false, multiple choice, and fill-in-the-blank) and presented to every participant in a random order during the administration of each test in an effort to prevent test sensitization.
Table 3.1. Pilot Study Design

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</tbody>
</table>

The independent variables of the pilot study were *GC 120 Section* (the between-subjects factor with three levels) and *Testing Occasion* (the within-subjects factor with two levels). *GC 120 Section* had three levels: a full treatment condition, a partial treatment condition, and a control condition. The dependent variables were *Test Score* (i.e., participants’ scores on the pretest and posttest), *Test Time* (measured in seconds), and *SW Exercise Grade* i.e., the grades that participants received on each SW assignment.

The pilot study took place over a two week period and made use of two class periods since all of the sections of *GC 120* only met once a week. Prior to the commencement of the piloting the participating *GC 120* instructors were informed of the intent and the methodology of the pilot study, and the researcher received answered any questions that they had. During the first class period for each *GC 120* section the participants were informed of the pilot study and the researcher answered their questions and afterwards the pretest was administered to participants in each of the study’s conditions. Following the administration of the pretest, the Full Treatment condition received access to tutorial videos demonstrating fully worked examples and partially worked examples, the videos’ associated exercises (e.g., clamp assembly, square block assembly, c-bracket assembly) which covered assemblies in *SW*, and the Pivot Assembly exercise which served as the far transfer problem. The Partial
Treatment condition received access to tutorial videos that only demonstrated partially worked examples, those videos’ associated SW exercises, and the pivot assembly exercise. The Control condition received access to the Full Videos and no far transfer problem.

After a preliminary exploration of the participants’ Test Scores, Test Times, and SW Exercise Grades, the data were cleaned. Overall, there was an improvement in scores between the pretest and posttest (see Table 3.2). Each condition observed its own increase in test scores with the control condition seeing the greatest gain in performance (see Figure 3.1). Test Scores were analyzed using a 3 x 2 mixed ANOVA with Testing Occasion as the within-subjects factor and GC 120 Section as the between-subjects factor. Although the interaction between Testing Occasion and GC 120 Section on test scores was non-significant, $F(2, 90)=2.93, p=.58, \eta^2_p=.061$, post hoc tests indicated that participants in the partial treatment condition scored significantly higher on the pretest than those in the control condition. There was a significant main effect of Testing Occasion on Test Scores, $F(1, 90)=16.81, p=.01, \eta^2_p=.157$. Post hoc tests revealed that the control condition experienced a significant learning gain between the pretest and the posttest.
**Table 3.2.** Means and Standard Deviations Across Conditions for Pretest and Posttest Scores.

<table>
<thead>
<tr>
<th>Condition</th>
<th>N</th>
<th>Pretest Score</th>
<th>Posttest Score</th>
<th>Gain Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Full</td>
<td>34</td>
<td>36.47 (10.12)</td>
<td>39.09 (8.79)</td>
<td>2.62 (13.29)</td>
</tr>
<tr>
<td>Partial</td>
<td>42</td>
<td>38.33 (7.94)</td>
<td>41.82 (6.91)</td>
<td>3.49 (9.78)</td>
</tr>
<tr>
<td>Control</td>
<td>34</td>
<td>34.12 (9.57)</td>
<td>42.00 (8.68)</td>
<td>7.88 (10.50)</td>
</tr>
<tr>
<td>Total</td>
<td>110</td>
<td>36.45 (9.25)</td>
<td>41.07 (8.90)</td>
<td>4.62 (11.37)</td>
</tr>
</tbody>
</table>

*Figure 3.1. Graph of Pretest and Posttest Scores.*

Prior to analyzing Test Times a log10 transformation was applied to the pretest and posttest Test Times data as a result of positive skewness. In general, Test Time increased
between the pretest and posttest even though the partial condition experienced a slight decrease in time (see Table 3.3 and Figure 3.2). A 3 x 2 mixed ANOVA was used to examine the potential differences in the transformed Test Times within and between the three conditions. There was no signification interaction between Testing Occasion and GC 120 Section on Test Time, $F(2, 91)=.637, p=.531, \eta^2_p=.034$. Moreover, post hoc tests indicated the following: 1) no significant differences existed between the conditions regarding their pretest times or their posttest times and 2) there not any significant differences in test time within each group.

**Table 3.3.** Means and Standard Deviations Across Conditions for Pretest and Posttest Times (measured in seconds).

<table>
<thead>
<tr>
<th>Condition</th>
<th>Pretest Time (Sec)</th>
<th>Posttest Time (Sec)</th>
<th>Gain Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>M (SD)</td>
<td>N</td>
</tr>
<tr>
<td>Full Treatment</td>
<td>42</td>
<td>136.81 (106.21)</td>
<td>39</td>
</tr>
<tr>
<td>Partial Treatment</td>
<td>43</td>
<td>141.93 (71.05)</td>
<td>44</td>
</tr>
<tr>
<td>Control</td>
<td>42</td>
<td>135.40 (96.80)</td>
<td>37</td>
</tr>
<tr>
<td>Total</td>
<td>127</td>
<td>138.08 (91.71)</td>
<td>120</td>
</tr>
</tbody>
</table>
The author evaluated the SW Exercises submitted by the participants in each GC 120 section using rubrics assessing the overall quality of the submissions as well as the requisite SW skills of the participants. The partial condition demonstrated the highest level of performance on the Clamp Assembly exercise relative to the other two conditions whereas the full condition scored higher on the Pivot Assembly than the partial condition (see Table 3.4 and Figure 3.3). A one-way ANOVA was conducted to determine if any differences were present in Clamp Assembly grades for the experimental conditions. There was a significant main effect for class section on Clamp Assembly grades, $F(2, 127)=3.859, p=.024, \eta^2_p=.057$. As there were unequal variances between each condition, the Games-Howell post hoc procedure was used to specify what differences existed. The post hoc procedure indicated
that the Full Treatment Condition had significantly higher grades than the Control condition but that the Partial Treatment condition had significantly higher grades than both the Full Treatment and Control conditions. Although the Full Treatment condition received higher grades on the Pivot Assembly exercise an independent t-test revealed that the Full Treatment condition and the Partial Treatment condition did not differ significantly, $t(59)=1.515$, $p=.135$ (2-tailed), $r=.19$.

**Table 3.4.** Means and Standard Deviations Across Conditions for Assembly Grades.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Clamp Assembly</th>
<th></th>
<th>Pivot Assembly</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>$M (SD)$</td>
<td>N</td>
<td>$M (SD)$</td>
</tr>
<tr>
<td>Full Treatment</td>
<td>40</td>
<td>74.63 (9.43)</td>
<td>40</td>
<td>67.88 (8.84)</td>
</tr>
<tr>
<td>Partial Treatment</td>
<td>48</td>
<td>79.17 (7.46)</td>
<td>21</td>
<td>64.29 (8.70)</td>
</tr>
<tr>
<td>Control</td>
<td>42</td>
<td>73.81 (12.49)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Total</td>
<td>130</td>
<td>76.04 (10.13)</td>
<td>61</td>
<td>66.64 (8.89)</td>
</tr>
</tbody>
</table>
The results of the pilot study indicated the viability of the instruments and proposed study methods, i.e., if the proposed study is executed in the same manner the potential for significant findings exist. One of the limitations of the pilot study was its timing, it was executed late within the Fall 2009 semester and for this reason some of the findings lacked statistical significance. A plausible reason for this is that the participants had learned and synthesized the main content for the GC 120 course by that point in the semester and had reached the steady state phase (see Chapter 2 for an explanation of this concept) of the
learning curve for the GC 120 coursework. If the proposed study occurs during the entire semester of GC 120 it is likely that richer results may occur because the study would encompass the entire body of coursework of GC 120. The pilot study experience was taken into account during the development of the proposed study’s methodology.

**Method**

**Participants**

A total of 161 students will participate in this study. All of the participants are students enrolled in two sections of GC 120, both sections are taught by Walter F. Kelly. The majority of the participants will be aerospace, civil, and mechanical engineering majors, and will have either sophomore or junior standing with the university. The age range of the participants will be between 19 and 21 years.

**Study Design**

The proposed study will be a quasi-experimental study because the participants are nested within both sections of GC 120. As there will be two quasi-experimental conditions, a treatment condition and a control condition, random assignment using a random number generator will determine which section of GC 120 is placed into each condition. The most prominent threat to the internal validity of the study is self-selection bias, which results from the participants being nested in a GC 120 class. For example, students with certain types of characteristics (e.g., intrinsic motivation, proficiency with CAD software) may have a propensity to enroll in the GC 120 section that is taught earlier in the day as opposed to the
section taught in the afternoon. This study will employ a 2 x 9 mixed design with a between subjects factor of experimental condition with two levels (treatment and control) and within subjects repeated factor with nine levels (9 Weekly Assessments). Please see Table 3.5 for the study design.

Table 3.5. Study Design

<table>
<thead>
<tr>
<th>Treatment</th>
<th>NR</th>
<th>O₁</th>
<th>X</th>
<th>O₂</th>
<th>X</th>
<th>O₃</th>
<th>X</th>
<th>O₄</th>
<th>X</th>
<th>O₅</th>
<th>X</th>
<th>O₆</th>
<th>X</th>
<th>O₇</th>
<th>X</th>
<th>O₈</th>
<th>X</th>
<th>O₉</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>NR</td>
<td>O₁</td>
<td>O₂</td>
<td>O₃</td>
<td>O₄</td>
<td>O₅</td>
<td>O₆</td>
<td>O₇</td>
<td>O₈</td>
<td>O₉</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Materials

There are several instruments that will be used during the execution of this study, they include the following: a Background Survey, nine Weekly Assessments, SW Activities, Lesson Overviews, and Tutorial Videos. The Background Survey collects demographic information (e.g., age, gender, university classification, and major) about the participants and has 11 questions and asks participants what solid modeling and drafting software packages they have familiarity with. Two of the questions are open ended. The remaining questions require participants to assess the current level of their drafting and solid modeling abilities using five point Likert scale responses and were adapted from Hamade and Artail’s (2008) survey of the technical attributes of CAD users. Weekly Assessments will be used to evaluate participants’ knowledge of SW content presented in this study and each Weekly Assessment consists of five questions randomly presented to participants in true-false format, multiple choice format, or fill-in-the-blank format, and each question is worth 10 points leading up to
a maximum of 50 points per Weekly Assessment. The multiple choice and fill-in-the-blank formats have four answer responses per question whereas the true-false format only has two.

All of the tutorial videos have SW Activities that coincide with them and there are also SW activities that participants in both experimental conditions are required to complete independently. All of the SW Activities are problems adapted from the GC 120 textbook authored by Bertoline and Wiebe (2002). The SW Activities corresponding to tutorial videos involve learners viewing the videos and using SW to replicate the modeling task that is demonstrated in the video. The independent SW Activities call for participants to apply the knowledge and skills that they receive from the tutorial videos to modeling tasks. Every lesson has one independent SW Activity that is a near transfer modeling task (*Near Transfer SW Activity*) that has similar characteristics to the tasks presented in the videos (e.g., a SW tool such as revolve will be used in the video and will applicable to the near transfer SW Activity) and one far transfer SW Activity (*Far Transfer SW Activity*) that shares no resemblance to the tasks in the videos and requires learners to generalize the skills that they have acquired from the tutorial videos to complete the task. There are SW Activities that a few randomly selected participants will be asked to complete in the presence of the researcher, these tasks are labeled *CTA SW Activities*. CTA SW Activities will be modeling problems adapted from the GC 120 textbook and participants will have their performance on these tasks recorded for analysis by the researcher.

Rubrics were created to ensure consistent evaluation of the Near Transfer SW Activities and Far Transfer SW Activities that are part of each lesson as well as the SW Activities that correspond to the tutorial videos. Every rubric delineates evaluation criteria
for all SW Activities and apportions a percentage of 100 total points to the objectives and focal points of the SW Activity, and provides a means of reliably grading the modeling task. All of the rubrics were reviewed by two CAD subject matter experts, Dr. Eric Wiebe and Dr. Ted Branoff, and received their approval before being incorporated into the study.

*Lesson Overviews* precede each tutorial video and display the objectives associated with each tutorial video as well as the objectives for the SW Activities. The Lesson Overviews associated with the tutorial videos show a picture of the goal state of the SW Activity (i.e., what the finished SW model or assembly is supposed look like), indicate the units that the SW Activity needs to be constructed in (e.g., inches or millimeters), and presents the objectives that the tutorial video is attempting to accomplish. The Lesson Overviews that are solely associated with independent SW Activities display a schematic of each activity and the units that the model should use.

Depending on the experimental condition to which participants are assigned the tutorial videos come in one of three formats: videos that demonstrate fully worked-examples of SW activities, videos that partially demonstrate worked-examples SW activities, and videos that fully focus on design intent. The former (referred to as *Full Videos* from here on) serves as a means of whole task practice because learners engage in the process of creating a solid model from beginning to end and it is during this process that they learn how problem solve in the context of constraint-based modeling and start to automate many of the procedural aspects of the modeling task. The treatment condition will receive access to Full Videos that have a multiple choice question and remediation at the end of the video. For example, if a participant answers the question correctly they will not receive remediation but
if the question is answered incorrectly then the participant will get remediation in the form of an extra video segment that explains what the correct answer to the question was and clarifies the concepts presented in the video. The partially worked-example tutorial videos (referred to as Partial Videos from here on) focus on automatization and refining participants’ procedural skills for SW modeling tasks e.g., a task may involve multiple extrusions and it is necessary that the process of creating an extrusion becomes intuitive to the learners. The videos that fully focus on design intent (referred to as Design Intent Videos from here on) are only introduced to participants in the treatment condition and these video emphasize design intent by presenting and demonstrating brief SW Activities that reinforce the process of embedding intelligence and functionality into a model. The Partial Videos and Design Intent Videos do not have remediation questions.

Paas’ (1992) unidimensional 9-point Cognitive Load scale (referred to as 9-point CL Scale from here on) will be used to measure the cognitive load imposed on participants by the SW Activities and Weekly Assessments. The 9-point CL Scale is symmetrical and adaptable, and asks participants about the amount of perceived difficulty they have experienced while completing a task. According to van Gog and Paas (2008, p. 18) this instrument has maintained a Cronbach’s Alpha ranging between .82 and .90 over the course of several cognitive load studies. It is an unobtrusive instrument in the sense that it requires a minimal amount of time to complete and does not have the propensity to disrupt participants’ engagement in the tasks that are apart of this study. The 9-point CL Scale administered in this study will require participants to fill out what GC 120 they are enrolled in, what lesson and SW Activity or Weekly Assessment they have just completed, and the instrument will
ask them the following question: “How much mental effort did you experience while completing the SolidWorks activity?”. The nine response choices range from “very, very low mental effort” to “very, very high mental effort” with “Neither low nor high mental effort” at the center of the scale. As participants’ responses on the 9-point CL Scale will be utilized in determining the amount of instructional efficiency that they experience, the responses will be coded from 1 to 9 during analysis.

All of the participants are enrolled in GC 120 they will be required to complete coursework not associated with the activities that comprise this study. For every lesson there is a weekly GC 120 Quiz that assesses the participants’ knowledge of the instructor’s lectures and the textbook readings that are assigned. Each GC 120 Quiz consists of 10 multiple choice questions that have a value of one point each. Since this study is quasi-experimental the GC 120 Quiz Grades will be used to determine if any selection bias exists between the participants in both experimental conditions. There is also a midterm exam and a final exam that the participants must take. The midterm exam consists of two components, a computer portion and a sketching portion. The computer portion is worth 60 points and incorporates multiple choice, true-false, and fill-in-the-blank questions as well as schematics that require participants to label sketch components. The sketching portion requires participants to sketch parts by hand on paper and is worth 40 points. Participants’ grades on the midterm exam results from combining the computer portion score with the score on the sketching portion. The final exam will consist of 100 questions presented in multiple choice and true-false formats, and the test will be scored out of 100 points.
Apparatus

The means by which the materials will be delivered to and accessed by the participants are described in this section. The course websites for both experimental conditions are housed on the NCSU Wolfware LMS and this is where participants will gain access to all of the materials (e.g., all of the various SW Activities, all of the various tutorial videos, Background Survey, and Weekly Assessments). The websites arrange each lesson in a hierarchical manner where all of the materials associated with a particular lesson are grouped together (see Figure 3.4). All of the Lesson Overviews will be produced using Microsoft PowerPoint and Adobe Presenter. Adobe Presenter has the ability to produce narrated and interactive multimedia presentations from PowerPoint files. Techsmith Camtasia Studio will enable the researcher to screen record SW demonstrations in order to create the tutorial videos. During the execution of the CTA SW Activities Camtasia Studio will be used to record the participants’ performance and the retrospective verbal protocols administered by the researcher. For the CTAs one Apple MacPro desktop computer with Techsmith Camtasia Studio installed on it will be used. A USB headset microphone will be used to record audio for the CTA. Adobe Captivate will be used to create all of the Weekly Assessments, and the remediation questions associated with the Full Videos.
Variables

**Independent Variables.** As this study has between-subjects and within-subjects factors it will use a mixed design. *GC 120 Section* (experimental condition) serves as the between-subjects factor and as each section will be assigned to either the treatment or control condition of this study this factor has two levels. The within-subjects factor is *Test Occasion* i.e., each administration of a Weekly Assessment. Test Occasion has nine levels because each of the nine lessons of the study has an assessment that coincides with it.
**Dependent Variables.** There are several dependent variables involved in the execution of the study: *Test Score, Test Time, SW Activity Grade, Cognitive Load, Instructional Efficiency, GC 120 Midterm Exam Grade, and GC 120 Final Exam Grade.* Test Score is a participant’s score on each Weekly Assessment and has a maximum of 50 points with each question being worth 10 points, and Test Time is amount of time (measured in seconds) that it takes for a participant to complete a Weekly Assessment. SW Activity Grade is evaluated out of a total of 100 points using rubrics that apportion a percentage of the points to each objective for the SW Activity. All SW Activities will be graded using rubrics by the researcher and a GC 120 instructor that is not involved in this study. Both sets of SW Activity Grades will be aggregated and the internal consistency (i.e., reliability) will be assessed using Cronbach’s Alpha. The cognitive load imposed by the Near Transfer and Far Transfer SW Activities as well as Weekly Assessments and the tutorial videos’ SW Activities will be measured by the 9-point CL Scale. Instructional Efficiency determines how participants’ performance on modeling tasks is associated with the amount of cognitive load imposed upon them and it is a combined measure of Cognitive Load, Test Scores, and SW Activity Grades. GC 120 Midterm Exam Grade is each participant’s score on the course’s mid-semester exam, which will likely be impacted by the content presented to the learners participating in this study. Similarly, GC 120 Final Exam Grade is each participant’s score on the course’s final exam at the end of the academic semester.

**Process Measures.** Process data is “information about what actually occurred during the implementation of an intervention” i.e., how portions of a study were executed and it is a necessary component of any well-designed study (McGraw et al., 1996, p. 292). It can assist
in the interpretation of a study’s results and understanding the presence or absence of significant findings. For the current study *Video Viewing Time* (measured in seconds), the amount of time a participant watches a tutorial video, and *Video Viewing Attempts*, the number of attempts that each participant makes to watch a tutorial video, both serve as a process measures.

**Procedure**

Each section of GC 120 meets for class once a week and this study will take place over the course of the entire 15-week Spring 2010 academic semester and will coincide with Lessons 2-7 and Lesson 11 of the GC 120 curriculum. One week prior to the commencement of the study the GC 120 instructor, Walter Kelly, will be briefed about how the study will be executed and any questions or concerns that he may have will be addressed. The briefing process includes a face-to-face meeting with Walter as well as a tutorial video for him that demonstrates how the materials of the study are to be administered via the Wolfware LMS, how participants are to be instructed to use the materials, and how completed SW Activities are to be uploaded to the Wolfware LMS. As the video will be accessed by the instructor using the GC 120 course website the researcher will be able to view the amount of time that the tutorial video has been viewed by the instructor. Also, weekly meetings where the researcher and the instructor discuss the administration and progress of the study will be arranged.

**Treatment.** The 005 section of GC 120 was randomly assigned to the treatment condition. At the beginning of the second class meeting of the semester the instructor will
inform students about the study and address any concerns that the students have about participating in the study. Next the instructor will distribute NCSU Institutional Review Board (IRB) Consent Forms that any students willing to participate in the study are required to sign and return to the instructor during the next class meeting. At the beginning of the third class meeting the instructor will collect the participants’ IRB Consent Forms and then will present the participants with the Background Survey and give them 10 minutes of class time to complete and submit it. Afterwards the Lesson 2 Weekly Assessment will be administered via the GC 120 Section 005 course website on the Wolfware LMS. The participants will always be given 10 minutes at the beginning of each class meeting to complete each Weekly Assessment and its associated 9-point CL Scale. At the beginning of each subsequent class meeting (except during Lessons 8 and 9, and when the GC 120 Midterm Exam is given) the instructor will administer a Weekly Assessment before beginning the day’s lecture and then make participants aware that the current lesson’s materials are now accessible on the Wolfware LMS. At every class meeting the instructor will make participants aware of the week’s lesson and materials, remind them to view the materials and complete the SW Activities, and answer any questions that the participants may have. Lessons 8, 9, and 10 have been excluded because those lessons’ content cover drafting and sketching, and have very little to do with solid modeling. As this is the case Lesson 11 has two Weekly Assessments associated with it, one to be administered immediately before Lesson 11 (similar to a pretest) and one to be administered after Lesson 11 (similar to a posttest).

Each lesson has Lesson Overviews and tutorial videos with associated SW Activities as well as one Near Transfer SW Activity and one Far Transfer SW Activity. For the
treatment condition each lesson includes a Full Video that encompasses the main SW content for the lesson, a Partial Video that emphasizes the procedural aspects of the lesson, and a Design Intent Video. The Full Videos for the treatment condition have remediation questions at the end of the SW demonstration. Although the materials for each lesson are presented to the participants in a hierarchical fashion via the GC 120 course website participants will be able to view the videos and complete the SW Activities for the current lesson in any order that they choose. All tutorial videos have a Lesson Overview associated with them that presents the objectives covered in the video and all completed SW Activities including the Near Transfer SW and the Far Transfer SW Activities will be uploaded to the Wolfware LMS by each participant. After completing each SW Activity and Weekly Assessment participants will complete a 9-point CL Scale. Every lesson’s SW Activities will be due nine days from the start of the lesson.

**Control.** The 003 section of GC 120 was randomly assigned to the control condition. At the beginning of the second class meeting of the semester the instructor will inform students about the study and address any concerns that the students have about participating in the study. Next the instructor will distribute NCSU Institutional Review Board (IRB) Consent Forms that any student willing to participate in the study are required to sign and return to the instructor during the next class meeting. At the beginning of the third class meeting the instructor will collect the participants’ IRB Consent Forms and then will present the participants with the Background Survey and give them 10 minutes of class time to complete and submit it. Afterwards the Lesson 2 Weekly Assessment will be administered via the GC 120 Section 003 course website on the Wolfware LMS. The participants will
always be given 10 minutes at the beginning of each class meeting to complete each Weekly Assessment and its associated 9-point CL Scale. At the beginning of each subsequent class meeting (except during Lessons 8, 9, and 10, and when the GC 120 Midterm Exam is given) the instructor will administer a Weekly Assessment before beginning the day’s lecture and then make participants aware that the current lesson’s materials are now accessible on the Wolfware LMS. At every class meeting the instructor will make participants aware of the week’s lesson and materials, remind them to view the materials and complete the SW Activities, and answer any questions that the participants may have. Lessons 8, 9, and 10 have been excluded because those lessons’ content cover drafting and sketching, and have very little to do with solid modeling. As this is the case Lesson 11 has two Weekly Assessments associated with it, one to be administered immediately before Lesson 11 (similar to a pretest) and one to be administered after Lesson 11 (similar to a posttest).

Each lesson has Lesson Overviews and tutorial videos with associated SW Activities as well as one Near Transfer SW Activity and one Far Transfer SW Activity. For the control condition each lesson includes only a Full Video that encompasses the main SW content for the lesson, this videos do not have any remediation questions associated with them. Although the materials are presented to the participants in a hierarchical fashion via the GC 120 course website they will be able to view the videos and complete the SW Activities for the current lesson in any order that they choose. The tutorial videos have a Lesson Overview associated with them that presents the objectives covered in the video and all completed SW Activities including the Near Transfer SW and the Far Transfer SW Activities will be uploaded to the Wolfware LMS by each participant. After completing each SW Activity and Weekly
Assessment participants will complete a 9-point CL Scale. Every lesson’s SW Activities will be due nine days from the start of the lesson.

**Cognitive Task Analysis.** Participants from both the treatment and control conditions matched by their responses on the Background Survey will be randomly selected to participate in the CTA portion of the study. Specifically, they will be matched based upon their 3D modeling experience, drafting experience, and university classification. Eight participants will be chosen, n=4 from the treatment condition and n=4 from the control condition. The students’ participation will be solicited via emailed by the researcher. Two CTA sessions will be administered by the researcher, one will focus on concepts from Lesson 4 and the other CTA will focus on Lesson 11 concepts. All CTA sessions will be individual sessions where the researcher meets with each participant one-on-one.

For the Lesson 4 CTA participants will be asked to perform two SW Activities in the presence of the research: the Far Transfer SW Activity, which they will have already completed for homework, and a novel Far Transfer SW Activity that they have not been exposed to. First, each participant will be informed of the CTA process and then the researcher will address any concerns that may arise. Next, the participant will perform the Lesson 4 Far Transfer SW Activity and their performance of the task will be recorded. After the performance is complete the researcher will engage the participant in a retrospective verbal protocol which will be recorded, this technique requires the participant to verbally explain every step of the modeling process that they executed while performing the Lesson 4 Far Transfer SW Activity. Lastly, the novel Far Transfer SW Activity associated with Lesson
4 will be performed and recorded, and a retrospective verbal protocol for this task will be requested from the participant and recorded.

The Lesson 11 CTA requires participants to perform the Lesson 11 Far Transfer SW Activity and engage in a retrospective verbal protocol about the task, both of which will be recorded. Afterwards the researcher will interview each participant about their GC 120 Final Project and how it was constructed in SW. The participants will also be asked to demonstrate how they assembled their GC 120 Final Project in SW and this demonstration and the interview will be recorded.

Two faculty members employed by NCSU Graphics Communication Program will serve as subject matter experts for both CTAs in order to establish benchmarks by which to assess the performance of the participants on the CTAs. The researcher will ask Dr. Eric Wiebe and Dr. Ted Branoff to complete the Lesson 4 Far Transfer SW Activity, the novel Lesson 4 Far Transfer SW Activity, and the Lesson 11 Far Transfer SW Activity. The subject matter experts will also be required to complete retrospective verbal protocols similar to the participants. By comparing the participants' performance and modeling process with that of the SMEs a better understanding of the mental models employed by the participants during SW Activities will be gained.

Data Analysis

Descriptive Statistics. Prior to primary data analysis using inferential statistics all quantitative data will be cleaned i.e., screened for anomalies and unexplained outliers and any observation lying outside of either two positive or negative standard deviations of a
variable’s mean will be disregarded. All of the dependent variables and process measures except for Instructional Efficiency will have their means, medians, modes, ranges, standard deviations, and standard errors examined and documented. As Instructional Efficiency is calculated using Cognitive Load, Test Score, and SW Activity Grades, this dependent variable will be examined independently.

**Inferential Statistics.** Before conducting any data analysis a Kolmogorov-Smirnov test of normality will be ran on all of the dependent variables’ data. This will determine whether parametric or nonparametric statistical approaches are required for data analysis. As this study utilized a 2 x 9 mixed design a mixed ANOVA will be used to analyze the following dependent variables: Test Score, Test Time, Cognitive Load, GC 120 Midterm Exam Grade, GC 120 Final Exam Grade, and Instructional Efficiency. Each mixed ANOVA will have its assumptions (e.g., Homogeneity of Variance) tested before being executed and if any assumptions are violated the appropriate post hoc procedure will be used (e.g., Bonferroni correction). Partial eta squared ($\eta^2_p$) will be the effect size measure for all of the mixed ANOVAs. As any measure of location (e.g., mean) would be ineffective in the assessment of participants’ Video Viewing Times because of individual differences and each participant’s unique study habits, a measure of dispersion such as the Levene Test will be used to analyze Video Viewing Times for each lesson.

**Cognitive Task Analyses.** The CTAs will be analyzed by examining and parsing the retrospective verbal protocols produced by the participants, and by creating task protocols of the participants’ performance on each CTA. The task protocols will consist of a listing of a participant’s actions during the SW Activity that was recorded and a time table delineating
when and how the actions were performed (e.g., accuracy). As the participants’ completed CTA SW Activity files will be saved they can be assessed for accuracy by the researcher and an independent grader. The task protocols will also be compared against the task protocols of the SMEs used to set the benchmarks for each CTA. As the data produced from the CTAs is rich and qualitative in nature it should aid in the overall interpretation of the findings from this study.
References


*Applied Cognitive Psychology, 10*(2), 151-170.


M. Marschark (Eds.), *Models of visuospatial cognition* (pp. 3-19). New York: Oxford University Press.


connections: The facilitative effects of diagrams on mental model development and

student comprehension of computer aided design (CAD) software principles. *Journal
of Industrial Technology, 18*(1), 2-7.

Boston, MA 02116: Allyn and Bacon.

reduce intrinsic cognitive load: Molar versus modular presentation of solution

worked examples be enhanced by instructional explanations and prompting self-
explanations? *Learning and Instruction, 16*(2), 104-121.

Knowledge acquisition for instructional system design. *Human Factors, 35*(3), 459-
481.

Hagman (Eds.), *Transfer of learning: Contemporary research and applications* (pp.

River, NJ 07458: Prentice Hall.


Understanding multimedia documents (pp. 103-118). New York City, NY 10013: Springer.


9-pt Cognitive Load Scale
How much mental effort did you experience while completing this GC 120 SolidWorks activity?

1. Very, very low mental effort
2. Very low mental effort
3. Low mental effort
4. Rather low mental effort
5. Neither low nor high mental effort
6. Rather high mental effort
7. High mental effort
8. Very high mental effort
9. Very, very high mental effort
Background Survey
GC 120 Background Survey

Name: ___________________________  Course Section: _________

Please complete this brief background survey. The information from this survey will be used to enhance the instruction provided to you from your GC 120 professor. The information that you submit will be confidential.

Age:  Gender:  Female  Male

University Class:  Freshman  Sophomore  Junior  Senior  Master  Doctor

Major:

1. I would rate my mechanical design skills as:
   - Non existent
   - Limited
   - Basic
   - Intermediate
   - Advanced

2. I would rate my familiarity with engineering graphics and drawings as:
   - Non existent
   - Limited
   - Basic
   - Intermediate
   - Advanced

3. At this point in time I would rate my 3D modeling skills as:
   - Non existent
   - Limited
   - Basic
   - Intermediate
   - Advanced

4. I would rate my familiarity with SolidWorks as:
   - Non existent
   - Limited
   - Basic
   - Intermediate
   - Advanced

5. What 3D solid modeling CAD software packages are you familiar with?
6. Have you previously taken any other 3D modeling courses prior to GC 120? [ ] Yes [ ] No
   If so, what courses and where (course/location)?

7. At this point in time I would rate my drafting ability as:
   [ ] Non existent
   [ ] Limited
   [ ] Basic
   [ ] Intermediate
   [ ] Advanced

8. What drafting software packages are you familiar with?

9. Have you previously taken any other drafting courses prior to GC 120? [ ] Yes [ ] No
   If so, what courses and where (course/location)?

10. I would rate my familiarity with feature-based modeling as:
    [ ] Non existent
    [ ] Limited
    [ ] Basic
    [ ] Intermediate
    [ ] Advanced

11. I would rate my familiarity with reverse engineering as:
    [ ] Non existent
    [ ] Limited
    [ ] Basic
    [ ] Intermediate
    [ ] Advanced