

DYNAMIC VS. STATIC VISUALIZATIONS FOR LEARNING
PROCEDURAL AND DECLARATIVE
INFORMATION

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in
Interdisciplinary Studies
International Cognitive Visualization

by
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DEDICATION

To my mother and father
for getting me here
and to my Aunt Gabeth
for countless tales of good advice.

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My research with Cisco gave me practical guidance that was eye opening, exciting and immensely helpful to me in understanding how research can and is used in real business situations. For this I owe a big thank you to my team at Cisco; Drew Rosen, Joseph Stratmann, Larry Engel, Kathy Yankton, Kevin Roderick, Ken Stanley you kept me smiling through this process and I am beyond grateful for the wonderful opportunity I had in working with all of you. I also offer a thank you to Belle Wei for setting up my first meeting with Cisco and believing that I was capable of following through with this project. I owe a big thank you to the faculty of the ICV program, thank you Dr. de Vries, Dr. Schwartz and Dr. Schnotz for expanding my mind and offering such insight into our field of research. I have grown more as a person and a researcher in these last years in the ICV program than I thought possible. A special thank you goes to my family for putting up with me during the toughest days of this rigorous research project. Finally I owe a thank you to my ICV colleagues for all of their support, companionship, encouragement and intellectualism. Sabine, Amy, Ulrich, Emeline, Jasen, Jen, Neil, Michael, Michele you have made this journey worth every moment through two years and three countries, Thank You!

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ABSTRACT

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The present investigation addresses the use of static vs. dynamic visualizations for learning declarative and procedural information under the topic domain of computer networking. One hundred and ten undergraduates were exposed to both procedural and declarative instructional material either in the form of static visualizations or dynamic visualizations. Participants were tested twice on both declarative and procedural information, once before exposure to the instructional material to measure baseline knowledge and once after exposure to measure information gain. The format of each test matched the nature of the information presented. The declarative test took the form of open-ended questions; the procedural test was a performance test. The results of this study indicated effects of visualization type for learning a procedure. Results are

discussed in terms of multimedia learning, and applied to the design of multimedia materials.

CHAPTER I

INTRODUCTION

Background

The belief that graphics benefit comprehension and learning is widespread (Hegarty, 2004; Mayer 2001, 2005; Schnotz, 2015; Tversky, Morrison, Betrancourt, 2002). Graphics have been shown to assist learning by allowing for dual coding when combined with text (Clark & Pavio, 1991), being aesthetically appealing and motivating, and graphics can at times save words especially for spatial relationships (Tversky et al., 2002). However, graphics come in many shapes, types and forms; notably relevant for the current investigation is the difference between static visualization and dynamic visualization. Static visualizations are still images, which do not move but can convey movement over time with multiple static graphics in combination. Dynamic visualizations are rapidly moving images such as animations or photorealistic videos. While there is widespread agreement that graphics benefit learning and comprehension, it is not clear that there is a discernable difference between static and dynamic visualizations.

In the present investigation, we address the issue of the relative merits of dynamic and static visualizations for learning, and offer a laboratory study to test static and dynamic visualizations on learning outcomes of declarative and procedural information.

Problem 1: Current theories of multimedia cannot explain nor accurately predict when

dynamic or static visualizations are most appropriate for a learning task. Problem 2: Previous research has not given enough attention to the type of learning task implemented, e.g procedural versus declarative learning tasks, nor to the topic domain. Problem 3: Procedural learning tasks used in previous research were relatively simple physical manipulations, which cannot be generalized to more complex or virtual procedures. Thus, the present investigation examines these problems by: a) identifying and differentiating between two common information types (procedural and declarative) and creating separate learning tasks comparing static and dynamic visualizations for each information type, b) creating appropriate tests for each type of information to be learned, and c) using the same, but relatively complex, topic domain of computer networking for both types of information – holding domain topic constant while varying the knowledge types.

Problems in Multimedia Research

Multimedia researchers (Hegarty, 2004; Mayer, 2005; Tversky, 2002) have attempted to understand when static or dynamic visualizations are best suited for learning using theories of working memory, cognitive load, cognitive theories of multimedia learning, and multimedia principles. Mayer (2005) proposed two contradictory hypotheses to understand the cognitive underpinnings of which type of visualization will better facilitate learning; the static media hypothesis and the dynamic media hypothesis. The static media hypothesis states that learning from static media will have deeper learning outcomes than dynamic media. The static media has its roots in cognitive load theory (Paas, Renkl, & Sweller, 2003; Sweller 2005) and the cognitive theory of multimedia learning (Mayer, 2001, 2005). Both theories are based on the premise that

attention is limited. Cognitive load theory identifies three types of cognitive processing:

- 1) Extraneous processing; cognitive processing that does not support a target learning goal;
- 2) Intrinsic processing; cognitive processing that involves attending to the important aspects of learning material; and,
- 3) Germane Processing; cognitive processing that involves deeper processing of the important learning material by means of mental organization and integration with prior knowledge.

Extraneous processing takes away from intrinsic and germane processing and negatively impacts learning. Accordingly, the static media hypothesis states that static visualizations and text enable learners to manage intrinsic processing by allowing the learners to control the pace and order of the presentation. Similarly, Hegarty (2004) proposes that dynamic visualizations present demands on human cognition that are not present in static visualizations. Hegarty (2004) expresses that heavy demands are placed on working memory when viewing dynamic visualizations because viewers cannot control the pace of visualizations. Viewers have to integrate transient information from frame to frame, which taxes limited memory.

Hegarty (2004) acknowledges that interactivity could solve some of the problem but states that by adding another tool this introduces more extraneous cognitive load. Mayer (2005) also posits that when viewing static visualizations, learners reduce extraneous processing by only seeing major steps of a process, which allows them to focus on key information. Furthermore, when viewing static graphics, learners are active processors. Learners have to elaborate or mentally simulate changes between frames in order to understand the complete process, which supports germane processing. Hegarty (2004) concurs, contending that mental simulation supports learning, while dynamic visualizations encourage passive processing. The sequence of dynamic visualizations is

predetermined and visually complete which does not encourage mental simulation and deep processing. In short, Mayer (2005) and Hegarty's (2004) previous stated hypothesis and theories suggest that static visualizations should predict higher learning outcomes than dynamic visualizations.

In contrast, Mayer (2005) lists some possible advantages of dynamic visualizations over static visualizations in what he terms the dynamic media hypothesis. First, dynamic visualizations require less cognitive effort to understand the initial message. Simply put, this is the opposite of mental simulation; a learner does not have to exert effort to mentally construct a dynamic representation because the external referent presents a complete visualization to the learner. Additionally, the pace and order of the presentation are predetermined so the learner does not have to exert effort to decide what to do. In this view, because the learner does not have to interpolate from frame to frame as with static visualizations, the viewer can concentrate on learning the task at hand. As we can see, cognitive theories of multimedia can be used to predict opposite outcomes. Mayer's (2005) static media hypothesis states that static visualizations should facilitate learning better than dynamic visualizations, while the dynamic media hypothesis directly contradicts the static media hypothesis by stating that dynamic visualizations should facilitate learning better than static visualizations.

To try to resolve contradictions between the static media hypothesis and the dynamic media hypothesis, Mayer (2005) ran a four-experiment study comparing static graphics and text to animations (dynamic visualizations) with narration and concluded that there was no support for the dynamic media hypothesis. Following an extensive literature review of studies comparing static to dynamic visualizations, there is little

consensus on when or if static visualizations or dynamic visualizations are more favorable (Mayer, Hegarty, Mayer, & Campbell, 2005; Carroll & Wiebe, 2004; ChanLin, 1998; Hegarty, 2004; Tversky, Morrison, Betrancourt, 2002; Hegarty, Kriz, Cate, 2003; Lee, Shin, 2012; Lowe & Schnotz, 2008; Arguel & Jamet, 2009; Ayres, Marcus, Chan, Ojan, 2009; Lowe, 2004; Michas & Berry, 2000; Schwan & Riempp, 2004; Spotts & Dwyer, 1996; Van Genuchten, Schieter, Schüler, 2012; Van Gog, Paas, Marcus, Ayres, Sweller, 2008; Wong, Marcus, Ayres, Smith, Cooper, Paas, 2009; Yang, Andre, Greenbowe, 2003). When looking to other reviews of relevant studies, the findings are equally equivocal. In a review by Tversky (2002), no advantage for dynamic visualizations over static visualizations was found. For the studies that did show an advantage for dynamic visualizations, Tversky (2002) pointed out that many of the visualizations were not informationally equivalent, with dynamic visualizations portraying more information than static visualizations, or the dynamic visualizations were confounded with other factors known to facilitate learning. And yet, Tversky (2002) recognizes that animations (dynamic visualizations) may facilitate the execution of a task rather than understanding of concepts. Further, animations may more effectively portray qualitative aspects of motion or microsteps, and the exact sequence of timing of complex operations. However, whether these aspects are better portrayed by animations is still unknown. The recognition that dynamic visualizations may facilitate the execution of a task implies that there may be some learning scenarios that are more appropriate for dynamic visualizations.

The research discussed above is focused rather narrowly on conceptual learning outcomes. However, in a meta-analysis by Höffler and Leutner (2007) in which 26

studies compared the instructional effectiveness of animations (dynamic visualizations) with static visualizations, three types of knowledge were distinguished: Procedural-motor knowledge, declarative knowledge, and problem-solving knowledge. The results showed an overall effectiveness of dynamic visualizations over static visualizations for both declarative and procedural-motor knowledge, with a marked advantage for the acquisition of procedural-motor knowledge. Höffler and Leutner's (2007) analysis contradicts previous contemporary research on instructional dynamic visualizations, which state that dynamic visualizations are usually unhelpful for learning. Inconsistencies in the literature on the relative superiority of static vs. dynamic visual images may be attributable, at least in part, to the fact that studies have failed to distinguish between procedural and declarative learning tasks.

A possible reason that dynamic visualizations show a learning advantage for procedural information over declarative information is in the nature of the learning outcome. Declarative learning outcomes take the form of recall of distinct facts and concepts, in predominately linguistic forms. Procedural learning outcomes take the form of action, of being able to correctly act out the appropriate steps in a particular order, for a finished result. Performance of actions (procedures) is arguably the most ancient and fundamental type of learning by humans. Such learning was accomplished by imitating and observing other more skilled people (Sweller & Sweller, 2006; Duchaine, et al., 2001). Indeed, Tversky (2011) points out that gestures and actions convey rich sets of meanings by using position, form and movement in space but like speech are fleeting and are limited by real time. With recorded dynamic visualizations, it is possible to make gestures and language permanent and repeatable, giving a learner the advantage of being

able to watch an expert perform a procedure more than once. Alternatively, exposure to a moving process is less relevant to declarative learning outcomes. Learning declarative information requires the ability to recall information linguistically implying that text and static graphics are more advantageous for learning declarative information.

The discrepancies in the literature comparing dynamic versus static visualization may be due to the differences in both the process of learning and the fundamental nature of procedural and declarative information. In the present investigation, we attempted to resolve the reasons for this discrepancy by investigating both procedural and declarative learning outcomes in the same study.

Problem two: Experimental Issues

When reviewing studies comparing static and dynamic visualizations, we noted multiple experimental issues. Previous research either looked at the acquisition of procedural information or declarative information, but never both within the same study. We believe it is important to look at both a declarative learning task and a procedural learning task within the same study to ensure that the differences between previous studies were not due to fundamental differences in experiments. By implementing both learning tasks within the same study, it is possible to control the way the static and dynamic visualizations differ from each other while ensuring that both visualizations are equated for both learning tasks. Similarly, previous studies have looked at a variety of different topic domains, ranging declaratively from explanations as to how electro-chemical principals operate in a flashlight (Yang et al., 2003) to how blood flows in a human heart (Spotts & Dwyer, 1996) and procedurally from demonstrations of how to tie a knot (Schwan & Riempp, 2004), to how to form a peptide chain (ChanLin, 1998). Thus,

it is difficult to compare static and dynamic visualizations when such a wide range of topics have been employed. Therefore, in the present investigation, we used the same topic domain of computer networking for both declarative information and procedural information. Finally, we found that most research comparing static versus dynamic visualizations for procedural information used relatively simple tasks. These tasks included tying a nautical knot (Schwan & Riempp, 2004), folding origami paper (Carroll & Wiebe, 2004), or performing first aid bandage techniques (Arguel & Jamet, 2009). The previously mentioned studies investigate physical procedures that are acted out in the environment. We wished to further test the boundaries of static and dynamic visual learning materials for a procedure by using a virtual procedure that takes place within a computer environment.

Overview of the Present Study

In the present study, we compared learning outcomes between static and dynamic visualizations for two different types of information to be learned—procedural and declarative—within the same topic domain. The topic domain chosen was computer networking. Declarative information consisted of factual information about the basic components of a computer network and procedural information consisted of instructions on how to set-up a basic computer network within a virtual computer environment. We chose to test both procedural and declarative learning material in the same study to ensure experimental control over the learning material and to regulate the way in which the static and dynamic visualizations differ. Similarly, we chose to use the same topic domain for both declarative and procedural information in order to keep procedural and declarative learning tasks as similar as possible. Previous studies have looked at a range of different

topic domains making it difficult to say if differences in learning outcomes between static and dynamic visualizations were due to the nature of the information being declarative or procedural or due to differences in topic domain.

In the present investigation, participants either saw only dynamic visualizations, or only static visualizations, and each participant saw both procedural and declarative information. Dynamic visualizations were computer-based animations with narration. We chose narration for the animation in accordance with Mayer's (2009) text modality principle, which states that when animations are to be combined with text, it is preferable that the text be spoken rather than written, in order to avoid split attention. As in previous studies (e.g. Mayer, et al, 2005), static visualizations were a series of static graphics with the narration presented as text.

In order to measure participant learning, participants were tested twice on both declarative and procedural information, once before exposure to the instructional material to measure baseline knowledge and once after exposure to measure information gain. The format of each test matched the nature of the information presented to ensure that the tests were appropriate gauges of learning. The declarative test took the form of open-ended questions, in which participants were expected to answer with factual information about basic components of a computer network. The declarative information presented was factual information; therefore, participants were expected to respond to questions with factual information. The procedural test matched the format of a procedure and was therefore a performance test. Participants were expected to perform 15 steps in order to set-up a virtual computer network; more steps correctly performed indicated a better understanding of the procedure.

Our literature review produced two contrasting hypotheses on whether static versus dynamic visualizations will foster higher learning outcomes. Mayer et al.'s (2005) static media hypothesis predicts that static visualizations will have higher learning outcomes than dynamic visualizations, while the dynamic media hypothesis predicts that dynamic visualizations will have higher learning outcomes than static visualizations. We believe that, due to a fundamental difference in learning procedural and declarative information, we will find support for both hypotheses in different situations. We propose that our ancestral history can be predictive of how procedures are best learned. Procedures historically have been passed to others by observation of other more skilled people, in which there is a complete visual referent of the to-be learned process. A dynamic visualization provides a complete visual referent of a process to a learner and therefore is better suited to learning a procedure than a static incomplete visual referent. Conversely, we propose that declarative information is primarily factual language that relies less on the visual referent and more on understanding the language concepts presented. Therefore, dynamic visualizations should not support the acquisition of declarative information; instead they should be distracting to the to-be learned concepts. This yields us with the following hypotheses:

Hypothesis 1. We expect to find support for Mayer's (2005) static media hypothesis that states that static visualizations will have higher learning outcomes than dynamic visualizations, but only for learning declarative information. Therefore, we predict that for learning declarative information, static graphics with text (static visualizations) will have higher learning outcomes than a dynamic video with narration (dynamic visualization).

Hypothesis 2. We expect to find support for Mayer's (2005) dynamic media hypothesis that states that dynamic visualizations will have higher learning outcomes than static visualizations, but only for learning procedural information. Therefore, we predict that for learning a procedure, a dynamic video with narration (dynamic visualization) will have higher learning outcomes than static graphics with text (static visualization).

CHAPTER II

LITERATURE REVIEW

Human Memory

Memory is essential to all healthy cognitive functioning and particularly important for human learning. Without a functioning memory system every human experience would be unfamiliar. Learning from and remembering past experiences are necessary to understand new experiences and help us decide how to behave. In order to understand human learning an understanding of human memory or the human cognitive architecture is fundamental. In this section the human cognitive architecture will be discussed using models of working memory and long-term memory with particular focus on distinctions between declarative and procedural memory

Short-Term Memory: Working Memory

Atkinson and Shiffrin (1968) theorized that human memory was comprised of three main parts; the sensory store, short-term store and long-term store. Sensory store is where information enters from the environment, short-term store is where new information is encoded with existing information, long-term store is where information is stored permanently with virtually unlimited capacity. Short-term store is generally described as having limited capacity and is commonly referred to as working memory due to its role in actively processing and encoding information. Baddeley's Multiple-

Component Model and Cowan's Embedded Process Model provide an overview of the functions of working memory that are relevant to learning from multimedia material.

Multiple-Component Model of Working Memory. Baddeley and Hitch (1974) like Atkinson and Shiffrin (1968) propose in their Multiple-Component Model of Working Memory (*Figure 1*) that information is processed in a serial order from sensory-store to working-memory to long-term memory. Baddeley and Hitch (1974) expand working memory by proposing three components within working memory. The three-component system was based on experiments that showed that participants could do a visual task and an auditory recall task concurrently without complete breakdown of capacity in working memory. These experiments led to two modality specific "slave systems" of limited capacity, the *phonological loop* and the *visual-spatial sketchpad*. The *phonological loop* stores auditory speech information and the *visual-spatial sketchpad* stores visual and spatial information. The third original component of working memory was the *central executive*, which controls encoding, retrieval strategies, and the allocation of attention. Later the *episodic buffer* was added to the model of working memory, which functions to hold and integrate episodes or chunks of multidimensional code, linking information in working memory with information in long-term memory (Baddeley, 2000). The Multiple-Component Model of Working Memory adds relevant information about how modality specific information is processed providing evidence that visual-spatial information and auditory information have separate limited capacity stores.

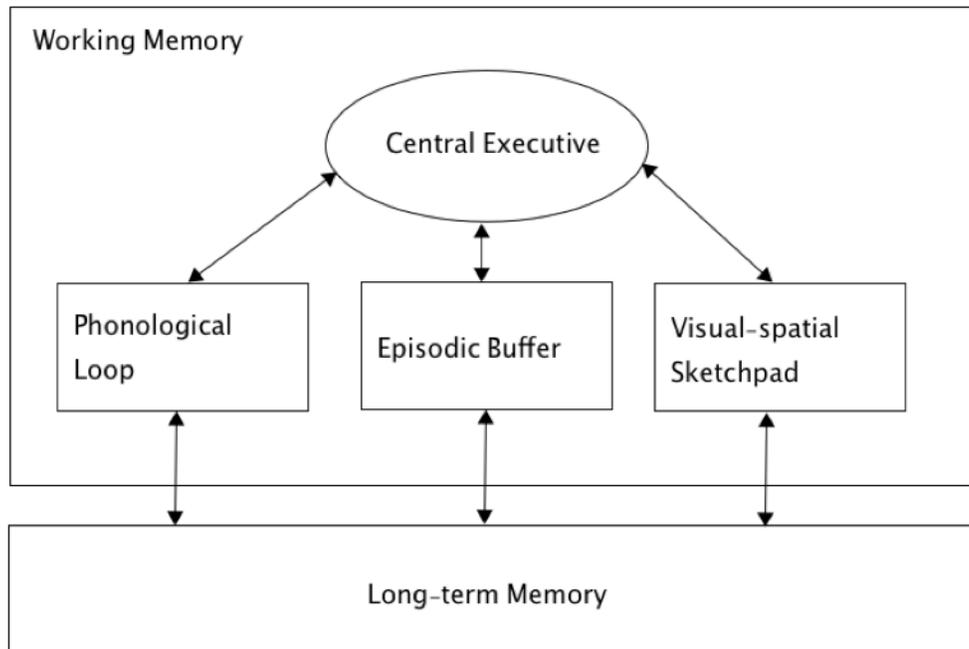


Figure 1. The Multiple-Component Model of Working Memory.
 Adapted from Baddeley, A. (2000). The episodic buffer: A new component of working memory?
Trends in Cognitive Sciences. doi:10.1016/S1364-6613(00)01538-2

Embedded Process Model of Working Memory. Cowan (1988) also theorized about the components of memory in the Embedded Process Model of Working Memory (*Figure 2*). The embedded process model differs from the previous models of working memory in that Cowan (1988) posits that working memory is an activated portion of long-term memory. Cowan proposes that within the activated portion of long-term memory (working memory) there is a small portion where attention is focused which has a limited capacity of about two to four pieces of information. Other parts of working memory hold activated information that people are not always aware of, including stimuli that are not changing in your environment very quickly. The embedded process model suggests that there is a central executive, which is neither a part of long-term memory nor

a part of working memory but works parallel to both long-term memory and working memory to direct attention and voluntarily control processing. Cowan (1988) places particular focus on control strategies such as verbal rehearsal and imagery imagination to explain how information is learned from empirically observed memory effects. In the embedded process model, processes are parallel instead of serial like in Baddeley and Hitch's (1974, 2007) and Atkinson and Shiffrin's (1968) models of memory. Both Cowan and Baddeley's model's stand today as modern conceptualizations of short-term memory, which explain the function of memory during learning from multimedia materials.

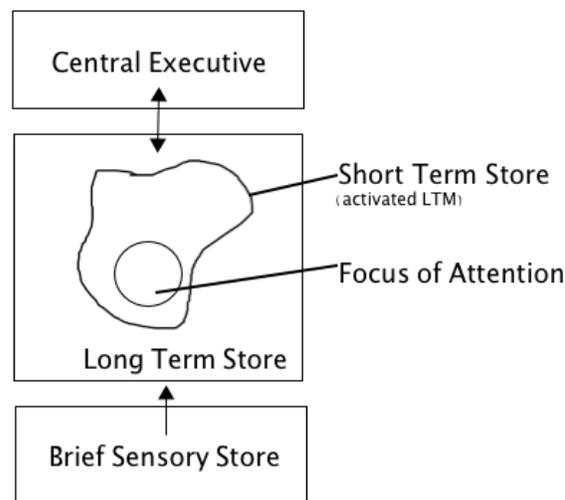


Figure 2. The Embedded Process Model of Working Memory. Adapted from Cowan, N. (1988). Evolving Conceptions of Memory Storage, Selective Attention, and Their Mutual Constraints Within the Human Information-Processing System. Psychological Bulletin, 104(2), 163–191.

Long-Term Memory

Long-term memory (LTM) is where information is stored for long periods of time. It is commonly believed that LTM has an unlimited capacity where information can

remain indefinitely. LTM is also proposed to have subcomponents. The beginnings of theorizing about LTM subcomponents can be seen in 1949, when Ryle distinguished between knowing how and knowing that. Winograd (1975) expanded on Ryle's (1949) distinctions and termed knowing how, procedural knowledge and knowing that, declarative knowledge. In 1962, Milner went beyond discourse and intuition about how human memory is divided by using experimentation. Milner (as cited in Squire, 2004) demonstrated that a hand-eye coordination skill called 'mirror-drawing' could be learned by an amnesic patient, H.M without H.M ever remembering having learned the task. Experiments with amnesic patients were the first to provide evidence that there were implicit and explicit memory systems that could work independent from each other. Commonly explicit memory is referred to as declarative memory and implicit memory is referred to as procedural memory. Declarative memory is defined as knowing that (propositional knowledge, factual information) while procedural memory is defined as knowing how (skills used to operate on the environment) (Anderson, 1983; Squire, 1986).

Declarative Memory. Declarative memory is considered to be knowledge and storage of facts and events (Squire, 1987; Tulving, 1985). Declarative memory is comprised of conceptual information and factual knowledge about a topic, which is termed semantic memory. Declarative memory is also comprised of events and experiences in the context in which they originally occurred, which is termed episodic memory. Declarative memory, both semantic and episodic, is knowledge that is conscious, explicit and representable (Tulving, 1987). Declarative knowledge is encoded in terms of relationships among multiple events and items; these relationships are

represented in the memory systems as networks of propositions. A proposition is the most basic unit of an event or item (Squire, 2004). Declarative knowledge can also be stored as images that preserve spatial relationships. Declarative memory is representational and provides a way to model the external world and as a model, the world is either true or false (Squire, 2004). Knowledge in the declarative system can be thought about and spoken about explicitly when a person directs their attention to their declarative knowledge. In order for a person to direct attention and consciously explicate facts the declarative memory system relies heavily on working memory (Crossley, Ashby, 2015).

Procedural Memory. Procedural memory is proposed as containing knowledge of how to do things in a step-by-step process placing particular emphasis on temporal order and spatial relationships (Anderson, 1983; Tulving, 1985; Squire, 1986). This is relevant to both physical procedures such as riding a bike or tying a knot and cognitive procedures such as playing chess, or giving a speech (ten Berge, 1999). Procedural knowledge is represented in memory as production systems, which are a set of productions or condition-action pairs (if-then statements). Production systems can be thought of as performance systems, which are neither true nor false and are expressed through performances rather than recollection (Anderson, 1983). One cannot simply add a production to their memory in the way that one can simply add a fact to memory. Adding a production or a procedure to memory occurs only in executing a skill one learns by doing (Anderson, 1983). Procedural skills once in memory are revealed and exist as reactivation of the production or performance (Squire, 2004). Typically, the process of acquiring a procedural skill takes many instances of doing to produce a fluent memory.

Once a procedure is learned and becomes a memory it is thought to be an automated process, which is not easily verbalized and shows its presence in the form of implicit actions (Anderson, 1983, ten Berge 1999; Brunyé, Taylor, Rapp, Spiro, 2006).

Distinguishing between procedural and declarative memory is not to say that procedural and declarative memory do not work together. The memory systems of the brain often operate in parallel to support behavior (Squire, 2004). For example we use declarative information to learn a procedure. By explicating steps of a procedure we are using declarative knowledge. Using explicit knowledge of a sequence about how to do something is declarative information. Being able to perform a procedure is procedural knowledge. Knowing what the '+' symbol means is declarative knowledge, while knowing how to add is procedural (ten Berge, 1999). As the foregoing example illustrates, we use declarative information to learn a procedure, demonstrating that the two memory systems work together during learning.

However, by reviewing procedural and declarative memory we can see that there are some fundamental differences in the way that procedural and declarative knowledge are stored, learned and expressed. Procedural knowledge is stored as performance systems (or production sets), while declarative knowledge is stored as networks of propositions (facts, images, or events). Procedural knowledge is learned by doing and usually takes multiple trials to become fluent in a skill while declarative knowledge can simply be added to memory. Procedural memory is automatic and implicit, while declarative memory is conscious, explicit and representable. Declarative knowledge is either true or false while procedural knowledge is neither true nor false. The goal state of learning a procedure is to be able to perform a task while the goal state of declarative

knowledge is to be able to explicate facts, events or concepts. The current view that the human brain is organized as a collection of specialized modules (working memory, long-term memory: procedural memory, declarative memory), with each module containing its own domain-specific knowledge and responses converges with the related field of knowledge known as evolutionary psychology (ten Berge, 1999).

Evolutionary Psychology

: Evolutionary psychology is psychology informed by the fact that the inherited architecture of the human mind is the product of the evolutionary process. It is a conceptually integrated approach in which theories of selection pressures are used to generate hypotheses about the design of the human mind, and in which our knowledge of psychological and behavioral phenomena can be organized and augmented by placing them in their functional context (Cosmides, Tooby, & Barkow, 1992, p. 7).

Evolution is the theory that there is a universal human nature, which evolved over millions of years to cope with adaptive problems (Cosmides, et al., 1992). In order to understand what the human mind is adapted to cope with and how it is organized it is important to understand the environment and problems our ancestors faced. Our ancestors evolved over the last two million years as Pleistocene hunter-gatherers (Cosmides et al.1992). This type of environment establishes that the type of adaptive problems that the human mind was shaped to cope with are Pleistocene conditions and not the modern world (Cosmides et al.1992) Evidence for this theory comes from the fact that if humans evolved more quickly we would see a difference between populations that have used agriculture for several thousands of years and those that have only recently adopted agriculture; however we do not see this difference (Cosmides et al.1992). Adaptive

problems that our ancestors evolved to overcome are problems that effect survival and reproduction (Cosmides et al. 1992, Geary, 2007). These problems include: finding mates, parenting, choosing an appropriate habitat, cooperating, communicating, foraging, hunting, and recovering information through vision (Cosmides et al.1992).

Consistent with the theory of evolution, our brain is a complex system, which emerged from a simple system through mechanisms of adaptation and mutation to address the aforementioned problems of survival and reproduction. Our brain addresses these problems by interacting with the environment and inputting sensory derived information from the environment, performing complex transformations of the input information and producing either representations or behavior (Cosmides et al.1992). In this way our brain is an information-processing system. Through the process of adaptation, nature “selects” (Darwin’s natural selection) one design over another, depending on how well it solves an adaptive problem that effects reproduction and survival (Cosmides, & Tooby, 1995). Therefore, in order to understand how the brain solves a problem it is important to understand which problems the brain was designed to solve.

Understanding movement information was crucial to the survival of our ancestors in many different ways. Our ancestors needed to be able to attend to and understand the movements of prey species, as well as predators in order to eat and evade danger (Duchaine, Cosmides, & Tooby, 2001; Geary, 2007). Our ancestors also needed to be able to learn skills such as how to hunt and tool making. Learning new skills was achieved through observation or instruction from other more skilled humans in the social environment (Geary, 2007; Sweller & Sweller, 2006). In this way humans evolved to

learn by imitating and observing other more skilled people (Sweller & Sweller, 2006). It was also important to be able to make inferences about other people's motives and future intentions by observing others' behavior and recognition of facial emotional states (Duchaine et al. 2001; Geary 2007). This evolved ability to infer other people's mental states is termed Theory of Mind ((Duchaine et al. 2001; Geary 2007). Understanding movement information was a crucial skill to the survival of our ancestors as was language in order to cooperate, learn and interact socially. Geary (2007) terms skills that humans have adapted to acquire "evolutionary primary knowledge." Evolutionary primary knowledge is knowledge that is more easily acquired and takes relatively little effort to learn. According to Geary (2007) both spoken language and visual movement information are part of human's evolutionary primary knowledge, and are therefore easily acquired with relatively little cognitive effort (Geary, 2007).

The importance of learning skills for survival and inferring movement information of other humans and species provides evidence that the knowledge of skills (how to do things) is older than the knowledge of facts; in other words procedural memory is older than declarative memory (ten Berge, 1999). Two scenarios provide further evidence. First, evolutionarily, by the fact that declarative learning (learning of facts) is only observed to occur in higher animals, if not human beings alone. The second, by the fact that children begin their learning by remembering procedures and movement information earlier than they learn and remember facts (ten Berge, 1999). Therefore we can safely assume that the most ancient way in which humans learned was procedural and the way procedural knowledge was obtained was by understanding and imitating movement information sometimes accompanied by verbal instructions.

Declarative memory is thought to have evolved as a part of procedural memory (ten Berge, 1999). The purpose of declarative memory enabled humans to learn the relation between stimuli presented and the sequence of events that occurred during that episode (Carlson, as cited in ten Berge, 1999). If we take the mathematical example that I used previously to describe the differences between procedural and declarative memory and how they work together it becomes clearer how declarative memory informs procedural memory. To know what '+' means is declarative knowledge of the meaning of a symbol; being able to add is procedural knowledge. Declarative memory of the meanings of symbols aids human memory in knowing which procedure to perform and when. Although mathematics is a relatively new idea in our evolutionary history, the aforementioned example illustrates how declarative memory and procedural memory interact and more importantly how the knowledge of symbol meanings can relieve procedural memory. In summary declarative memory is thought to be evolutionary younger than procedural memory and to have evolved from procedural memory in order to aid humans by retaining an explicit memory of relations of stimuli and sequence of events (episodic memory) as well as the recognition of symbols which represented procedural aspects and language.

Symbol recognition is declarative knowledge and is the basis of all written language. In terms of evolution, written language is a much more recent development than observing movement and spoken language. Written language dates back only about 5,000 years and literacy has only become a common skill among humans in the last 200 years. Written language is a complex system of symbols, which evolved from spoken language, in order to make spoken language more permanent. The origins of written

language are in pictures which overtime have become abstracted from their original intended meaning (Tversky, 2002). The understanding of these symbols is declarative knowledge. The advantage of written language is that it is not ephemeral, unlike spoken language. Written language can be coded and retransmitted hundreds to thousands of times, limited only by the language itself and levels of literacy. Written language is a great and recent advantage for humans in their ability to share information and to be able to review information. This is particularly advantageous for the transmission of declarative information, due to the fact that knowing the meaning of a specific symbol is declarative knowledge. This indicates that for learning declarative information, written language with pictorial diagrams may have a particular advantage. This advantage stems from the fact that the information presented is repeatable, and permanent, giving a person the ability to review the information as many times as necessary to encode the information into memory and the way in which the information is presented (written symbols) corresponds to the type of information (declarative) being learned.

However, learning from spoken language and observation of movement are the most ancient and effective means of transmitting procedural information (Duchaine et al. 2001; Geary, 2007; Sweller & Sweller, 2006). From these observations we might conclude that the best way to learn a procedure and the best way to learn declarative information may be fundamentally different. In the next section we will use theories of mental simulation and mental imagery to explain how information is encoded into the brain while watching and performing a procedure. Next, we will use Dual Coding Theory and Schema Theory to explain how declarative information is encoded and organized in the brain.

Theory of Grounded Cognition

Theories of evolution help to explain the importance of observation in learning a procedural task, in that observing and learning a skill was crucial to the survival and reproduction of our human ancestors. The Theory of Grounded Cognition focuses on the role of simulation in cognition and the production of mental imagery, which can explain how the brain facilitates learning by observation (Barsalou, 2008). “Simulation is the reenactment of perceptual, motor, and introspective states acquired during experience with the world, body, and mind” (Barsalou, 2008 pg. 618). Mental imagery is the conscious construction of representations in working memory (Barsalou, 2008). As a person experiences an action the brain captures states across the modalities such as how the action looks, and feels and integrates them with a multimodal representation of the action and stores this in memory (Barsalou, 2008). Whenever a person thinks about this action, the multimodal representation which was captured during the experience is reactivated to mentally simulate how the brain represented the action and the feelings associated with it (Barsalou, 2008). Mental Imagery is the deliberate attempt to construct these representations in working memory, such as what happens when a person deliberately tries to learn a procedure (Barsalou, 2008). Mental imagery and mental simulation help explain how viewing expert models perform a skill facilitates learning.

Expert performances of procedural tasks facilitates learning in that it helps the brain create a mental simulation of the action that is to be acquired and primes the execution of a similar action (Barsalou, 2008; Van Gog et al., 2008). Visualizations automatically trigger this simulation process, which is thought to be effortless and require little cognitive load (Van Gog et al., 2008). This explains why viewing movement is

perceived as requiring less mental effort than reading a text or interpreting a static diagram.

How the brain is able to mentally simulate action is explained with theories of a human mirror neuron system (Barsalou, 2008; Van Gog et al., 2008). The human mirror neuron system consists of cortical circuits in the brain that have a mirroring capacity which is activated by observing motor actions made by others (Van Gog et al., 2008). This means that the same circuits that allow a person to execute an action also respond to observing someone execute a task (Van Gog et al., 2008). The mirroring allows for priming or preparing the brain to be able to perform the observed task. Furthermore, the mirror neuron system is thought to play a role in inferring intentions of an action (Van Gog et al., 2008). Inferring intentions allows a person to not only imitate the task but also to understand why the person is doing it. This allows for transfer and application of what has been seen and learned to new tasks and contexts (Van Gog et al., 2008). In this way a person can infer the goal of an action and not only imitate the action but choose a different way of achieving the goal (Van Gog et al., 2008). Mental simulation and mental imagery also explain the importance of action information in learning a procedure. Seeing action information facilitates the brain in creating mental imagery of an action. This should be especially true in novice situations, where the learner is acquiring the skill for the first time and does not have any prior knowledge of the action states. Viewing an expert perform a skill that is to be acquired helps the brain identify action states and then to mentally simulate the actions needed to carry out the skill. The brain can then store mental simulations in memory as a memory trace. This memory trace can then be reactivated at a later time when performing the action.

The theory of grounded cognition is particularly relevant to learning a procedure. This theory explains through mental simulation and mirror neurons how the brain takes an observation of a procedure and stores the procedure in memory.

Schema Theory & Dual Coding Theory

Before we begin this section we want to reiterate that declarative knowledge and memory is thought to have evolved from procedural memory in order to remember stimuli in relation to events in time and to remember and understand symbol systems. Therefore declarative information is commonly used in the process of learning a procedure. The next section reviews theories of encoding, storage and retrieval of declarative information. Declarative and procedural memories are not mutually exclusive and commonly work together towards common goals. Remember that knowing what a symbol means is declarative knowledge and knowing how to read is a procedure that once learned is automated.

Schema Theory

Schema theory (Alba & Hasher, 1983; Anderson & Pearson, 1984) was derived from theories on reading comprehension. Symbols and written language are largely declarative information and theories on reading comprehension try to understand how we make sense of symbols and written language presented to us. Schema theory most closely corresponds to how humans learn declarative information. Schema theory explains encoding, storage and retrieval of information and knowledge into memory in terms of a schema. A schema is a data structure that represents a hierarchical organization of nodes or generalized categories. Successful encoding requires that, relevant information is

selected from the environment. A subset of the information that was selected is then transformed from modality-specific representations into units of meaning. The relevance of new information is evaluated and may be recognized as similar to an existing node, which activates related schema where the incoming information will be stored. The units of meaning are then interpreted and integrated with respect to existing knowledge (existing schema). Storage of schema in long-term memory is proposed by schema theories to be hierarchical and generalized. Retrieval of schema in long-term memory is a process of reconstruction. Nodes represent memory traces in an activated schema based on the content of memory and presented stimuli.

Dual-Coding Theory

Dual-Coding Theory (DCT) (Clark and Pavio, 1991) similarly suggests that knowledge is stored in long-term memory as an associative structure or network of interconnected nodes. DCT like Schema Theory is most relevant to the encoding of declarative information, in that it deals with conscious meaning-making and explicit activation of related networks of information selected from the environment. Recall that declarative information is often used to teach a procedure (verbal specifications of the steps of a procedure). According to DCT (*Figure 3*), activated nodes and their connections constitute meaning. The main difference between DCT and Schema theory is that DCT posits that there are two subsystems in long-term memory: the verbal store, and nonverbal store. The verbal store contains semantic representations of linguistic stimuli, which are processed in a sequential manner and termed by Clark and Pavio (1991) “logogens.” The nonverbal store contains modality-specific items (visual, auditory, tactile, or other sensory specific information) termed “imagens”. Clark and Pavio (1991)

were the first to point out that due to the separate verbal and nonverbal subsystems proposed in their theory that the combination of visuals and some form of language (written or spoken) should enhance learning.

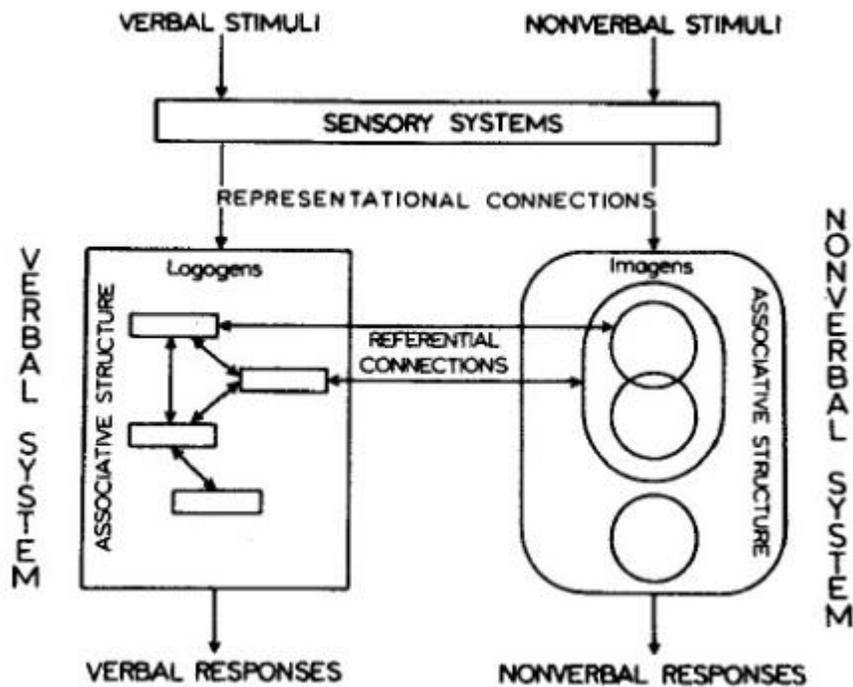


Figure 3. Structural Model of dual coding theory. Adapted from *Mental representations: A dual coding approach* by Allan Paivio. Oxford University Press, Inc.

Thus far we have reviewed the human cognitive architecture, differences between procedural and declarative knowledge, and differences in how procedural and declarative memories are formed, stored and retrieved. For procedural information to become a memory, it is important for the learner to view action information that stimulates mental

simulation. Learners use mental imagery to consciously remember the steps and actions of a procedure in working memory, which is used to create a memory trace that after practice becomes an automated memory. Once the memory becomes automated the procedure or skill does not require conscious attention to reactivate. Declarative information becomes a memory by attending to the declarative information in working memory and integrating it into existing schema or networks of similar information in long-term memory. To retrieve declarative information from memory one must consciously activate the schema where the information is stored. Next we will review research in multimedia, which integrates theories of human cognition, memory and learning with experimental research to understand how humans learn from external stimuli.

Multimedia

An important issue in the study of learning information involves determining effective methods for building strong representations of information in memory that will lead to reproducible and reliable outcomes. In this section we will review research on multimedia, which attempts to understand the ways in which we learn from stimuli in our environment, specifically instructional material. Multimedia research endeavors to find the best ways to present information for learning and instruction and provides advice for the design of new instructional material. This section will specifically focus on research with dynamic and static visualizations.

Multimedia is defined as any presentation that combines more than one format (words and pictures), this can be in a single sensory modality (visual display with pictures and text) or across modalities (visual display with spoken narration) (Brunye, et

al., 2006). Models of learning from multimedia use the components of human memory to explain the processes required to integrate incoming information from multiple formats and modalities into a single coherent mental representation of the information. A common theory used to explain how this occurs is Dual Coding Theory (DCT). DCT has been refined and added to by Mayer's (2001) Cognitive Theory of Learning From Multimedia (CTLM) and Schnotz (2015) Integrated Model of Text-Picture Comprehension (ITPC). The basis of these theories is that when graphics and text are combined the information presented is dually coded, being processed both through verbal and non-verbal channels. When information is dually coded, such as when you have text and pictures, there is a redundant encoding which increases the probability of retrieval at a later time. The enhancement of learning by presenting both verbal and non-verbal information was termed The Multimedia Effect (Mayer, 2009). The Multimedia Effect proposes benefits to presenting verbal information and non-verbal information simultaneously. These theories support not only the benefits of text and graphics but of verbal and non-verbal information being presented simultaneously. This can also take the form of audio verbal information and some form of visualization.

Visualizations with some form of language are commonplace in instructional material and appear in a variety of mediums, including books, websites, animations, and videos. A common distinction between types of visualizations is dynamic and static. Dynamic visualizations are visuals that are a series of moving images that change over time such as animations or videos. Static visualizations are visuals that do not move and stay the same over time. Change over time may be shown as a series of static visualizations but the images themselves do not move. Recent research has begun to look

at the distinctions between dynamic and static visualizations, and when and if dynamic visualizations are superior to static. As we review the literature on dynamic and static visualizations it is important to consider the learning goals within specific studies. It must be considered that learning a procedure is different from learning declarative information. Importantly, learning a procedure, tests in the format of action, of completing a procedure correctly by making sure the appropriate steps are acted out in a specific order. Learning declarative information, such as learning about the parts within a braking system (Mayer, 1990) tests in a format based on recall of information and knowledge about how different parts relate to each other.

An extensive literature review was carried out investigating studies comparing static to dynamic visualizations. What we found by looking at these studies is that there is little consensus on when or if static visualizations or dynamic visualizations are more favorable (Mayer, Hegarty, Mayer, & Campbell, 2005; Carroll & Wiebe, 2004; Chanlin, 1998; Hegarty, 2004; Tversky, Morrison, Betrancourt, 2002; Hegarty, Kriz, Cate, 2003; Lee, Shin, 2012; Lowe & Schnotz, 2008; Arguel & Jamet, 2009; Ayres, Marcus, Chan, Ojan, 2009; Lowe, 2004; Michas & Berry, 2000; Schwan & Riempp, 2004; Spotts & Dwyer, 1996; Van Genuchten, Schieter, Schüler, 2012; Van Gog, Paas, Marcus, Ayres, Sweller, 2008; Wong, Marcus, Ayres, Smith, Cooper, Paas, 2009; Yang, Andre, Greenbowe, 2003). We believe this is due in part to the lack of distinction between the learning goals of experiments. Studies that have failed to show an advantage for dynamic visualizations involve learning tasks of conceptual declarative knowledge. These studies focused on natural processes including concepts of the development of lightning, meteorological dynamics, and how the tides work (Lowe & Schnotz 2008; Mayer 1990).

In a study using the learning topic, meteorological dynamics (Lowe & Schnotz, 1991, 2008) it was pointed out that the visible dynamic changes that were shown in the dynamic visualization did not directly connect to the underlying causal principles that needed to be learned in order to understand the weather map (Lowe & Schnotz, 1991, 2008). This is important when discussing the benefits of learning from dynamic visualizations; again we need to be conscious of what the learning goal is and how information is being depicted. A dynamic visualization does not always best convey the relevant information to be learned. Hegarty (2004) points out that dynamic visualizations can be too fast for a learner to comprehend the information presented and can overload working memory (Hegarty, 2004). When a person views a dynamic visualization, a person can only view one frame at a time, once the visualization has moved past a frame, it is no longer available to a viewer. Encoding and comparing stimuli takes in the tens of hundreds of milliseconds, which places heavy demands on the limited capacity of working memory (Baddeley, 2007; Hegarty, 2004). This demand is due to the necessity of information from previous frames being integrated with new information at a quick pace, which may be unattainable due to the rapid speed of video frames (Hegarty, 2004). This may be especially true for learning declarative information from dynamic visualizations because unlike learning a procedure the action information is not as crucial to the learning task. The rapid pace of information does not give a learner of declarative information time to re-inspect pertinent information and integrate this information into working memory. In a four-experiment study Mayer (2005) found support for static over dynamic visualizations for learning four separate topics of declarative information. Tversky et al., (2002) demonstrated in a review of experimental studies on static versus

dynamic visualizations that animations (dynamic visualizations) are not superior to static diagrams in facilitating learning of factual information about complex systems (declarative information).

In contrast to Tversky (2002), a meta-analysis of 26 studies comparing instructional effectiveness of animations (dynamic visualizations) with static pictures by Höffler & Leutner (2007), showed an overall effectiveness of animations over static visualizations for both declarative and procedural knowledge, with a marked advantage for the acquisition of procedural knowledge. Procedural tasks including knot tying, assembly, first-aid procedures, and puzzle construction with results showing an advantage for dynamic over static visualizations (see e.g., Arguel and Jamet 2009; Ayres et al. 2009; Lee & Shin, 2012; Park & Hopkins 1993; Wong, Marcus, Ayres, Smith, Cooper, Paas, 2009). A possible reason that dynamic visualizations may have an advantage over static visualizations for learning a procedure is due to the fact that dynamic visualizations display action information necessary to understanding the task. Michas and Berry (2000) reported that the effectiveness of different combinations of media for learning a procedural task was directly influenced by the extent to which the media conveyed action information. This relates back to theories of evolution as well as theories of mental simulation and mental imagery. Dynamic visualizations that depict relevant action information of the procedure allows for humans to learn by observing and mentally simulating relevant actions. We know that from an evolutionary point of view this is the most ancient way to learn a procedure and from theories of grounded cognition that this process is automatic and requires little cognitive effort.

Further this review supports the assertion that static visualizations maybe better than dynamic visualizations for learning declarative information, due to the heavy demands placed on working memory by dynamic visualizations rapid pace and constantly changing information. Learning declarative information relies more heavily on language and complex symbol systems in order to understand explicit factual or conceptual information. Due to the heavy reliance on interpreting explicit symbols and language, learners may require more time with learning material which suggests that static graphics and text will be more advantageous for learning declarative information.

Conclusions

This review indicates first that there are differences in the components of human memory, which identify a procedural memory component and a declarative memory component. Procedural memory is ‘learning how’ while declarative memory is ‘learning that.’ The differences in these memory systems stem from human’s evolutionary history that indicates that procedural memory is the oldest form of memory that evolved so that humans could learn skills and infer movement from other humans and species. The most basic and ancient way in which procedural information enters into memory is by direct observation of action information, which is mentally simulated and stored as a memory trace. Declarative memory evolved from procedural memory in order to help humans cope with and remember specific episodes and to interpret symbol systems. Declarative information enters memory with conscious effort and is stored in related networks of schemas in long-term memory. Procedural memory and declarative memory often work

together to achieve common goals; that is, declarative information is often used to learn a procedure.

Based on the differences in procedural and declarative knowledge – the nature in which each are encoded, stored and retrieved from memory – different types of learning materials are more appropriate to learning different types of information. Specifically learning a procedure is best accomplished by observing another person perform that skill, supplemented by the spoken word. For the acquisition of declarative information there is a root in written symbol interpretation and pictorial diagrams.

Dynamic and static visualizations are common ways of presenting information. In research on learning from multimedia we see a marked difference on the effectiveness of the use of dynamic and static visualizations for learning. Dynamic visualizations show an advantage for learning a procedure while static visualizations shows an advantage for learning declarative information. A possible reason for this is in the nature of the learning outcome. Declarative learning outcomes take the form of recall of facts and concepts, in static and predominately linguistic forms. Procedural learning outcomes take the form of action, of being able to correctly act out the appropriate steps, in a specific order, for a finished result. Gestures and actions convey rich sets of meanings by using position, form and movement in space but like speech are fleeting and are limited by real time. With recorded dynamic visualizations, it is possible to make gestures and language permanent and repeatable. This gives a learner the advantage of being able to watch an expert perform a procedure repeatedly. Viewing moving processes is less relevant to declarative learning outcomes. Learning a declarative task requires the ability to recall information

linguistically or with a static diagram. This implies that text and static graphics are more advantageous for a declarative learning task.

This study attempts to understand when dynamic versus static visualizations are best suited for learning procedural versus declarative information as well as expand on findings from previous studies. In previous studies on learning a procedure, the task was relatively simple (learning to tie a knot, origami paper folding) and relied on showing action information. The current study attempts to find out if dynamic visualizations are better than static visualizations for learning a more complex procedure (how to set-up a virtual computer network) on a computer, with the action information being visual mouse movement and clicks. This study also includes both presentation of procedural information and declarative information within the same topic domain (computer networking). In order to keep the tasks as similar as possible, only the type of task: procedural or declarative is varied. In line with the findings of Höffler and Leutner (2007), we expect that dynamic visualizations will prove more effective in fostering the acquisition of procedural knowledge. In line with Mayer (2005) we expect that static visualizations will prove more effective in fostering the acquisition of declarative knowledge.

CHAPTER III

METHODOLOGY

Design

The present study is a pre-test, post-test, 2-visualization (dynamic video vs. static graphic) x 2-type of information (declarative vs. procedural) partial within-subjects factorial design. This resulted in four experimental conditions (Table 1.): declarative – procedural static graphics; procedural – declarative static graphics; declarative – procedural dynamic video; procedural – declarative dynamic video. Each participant saw either only static-graphic visualizations or only dynamic-video visualizations and each participant saw both declarative and procedural instructional material.

Table 1.

Experimental Design

	Procedural – Declarative	Declarative – Procedural
Dynamic	27	28
Static	28	27

Participants

The participants were 110 college students, 84 recruited from the Computer Science Department and 26 from the Psychology Department at California State

University, Chico. Participants were offered course credit for their participation. There were 36 females and 74 males. The mean age was 21.64 ($SD = 5.02$), with a range from 17 to 50. The mean GPA was 3.13 ($SD = .52$), with a range of 1.80 to 4.00. The participants consisted of 44.5 % Caucasian, 1.8% African, 27.3% Latin American, 1.8 Pacific Islander and 24.5 % other or prefer not to say. Participants were randomly assigned to each of four conditions.

Materials

The materials used in this study included experimental instructional material consisting of two sets of static graphics and two sets of dynamic videos – one set of each for the declarative information, and another set of each for the procedural information; a pre and post-test for both the declarative and procedural information; a demographic survey, and an end of study questionnaire. A website was built with these materials to implement the study. All materials for the study were created by the researchers (see: Analysis of the Domain).

Analysis of the Domain

An analysis of the domain of computer networking was carried out in order to create accurate material for the study. The current study consisted of two primary topics; declarative (factual) information about the components of a computer network and procedural information on how to set up a basic computer network. New instructional material was created for each topic (declarative and procedural information).

Declarative Analysis

To create the declarative materials for the study, we first had to identify relevant and accurate factual information about computer networks. To do this, we broke down a computer network into its component parts. This resulted in five physical components and four non-physical components. The physical components were: a router, two PC's, a switch and connecting cables. The four non-physical components were: IP addresses, subnet masks, configuration and routing protocols. Each component was then broken down using the structure-behavior-function (SBF) representation, a method created initially by Goel et al. (1996) and expanded by Lie and Hemelo-Silver (2009) that supports deep understanding of complex systems. Within SBF, structure refers to the elements of a system, behavior refers to the mechanisms within a system, and function refers to outcomes or roles in a system. For example, the computer component of a router would be one of the structures of a computer network. The behavior of a router is to receive and move data packets between devices. The function of a router is to allow communication among devices including other routers. Each component of the computer network was broken down in this manner, which was used to make the script for the narration of the dynamic video. Components and facts about each component came from Cisco Systems professional instructional materials and were also fact-checked by an expert in the field.

Procedural Analysis

For the creation of the procedural materials within the domain of computer networking, the procedure chosen was how to set up a basic computer network. In order for participants to be able to demonstrate knowledge of the procedure, and to be able to

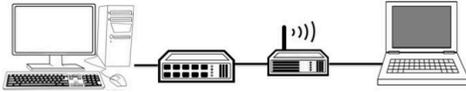
test knowledge easily, the computer software program *Packet Tracer* was chosen to be used for the procedural portion of our study. *Packet Tracer* is a computer software program used by Cisco Systems to train individuals virtually on how to set-up computer networks. A Cisco Systems professional who specializes in the use of *Packet Tracer* created a dynamic video specifically for this study. In order to construct a dynamic video specific to the study, we decided to use the most basic components of a computer network that are needed to have two computers communicate with each other. The most basic components of a computer network were identified using Cisco Systems Professional Instructional Material, and was confirmed by a professional in the field. The virtual computer network components demonstrated in the procedure were the same computer network components explained declaratively with the declarative materials.

Declarative Condition

Dynamic Video. The declarative instructional dynamic video was created using Adobe Captivate 8. Visualizations were created that corresponded to information in the script and which adhered to Mayer's (2009) design principles of multimedia. Visualizations included animated graphics and computer screencast video clips. The script was narrated by a male voice, which was overlaid with the relevant visualizations; this formed the declarative dynamic video. The subject of the dynamic video was “Basic Components of a Computer Network” and contained factual information about each component of a computer network. The dynamic video’s dimensions were 1110 x 832 dpi and lasted for eight minutes and five seconds. Participants were allowed to watch the video only once and could not pause or rewind it at any time.

Static Graphics. From the declarative dynamic video, a set of declarative static graphics were created. A total of 43 still images were chosen from the declarative dynamic video of the pertinent information displayed. The script for the narration in the dynamic video was used as the text-base and matched to each still image. This resulted in a set static graphics with consistent text located directly under the static graphic. Each static graphic, with matching text, was displayed on a separate webpage. In order to proceed to the next static graphic, a participant could either click a “next” button, or the website would automatically redirect to the next webpage after an allotted amount of time. The amount of time per page was determined by how much time was spent on the same information in the declarative dynamic video plus 20% to account for reading time. The 20% increase was determined by feedback from participants in a norming study, which initially had no increase in time; and, participants found they did not have enough time to both read the text and view the static graphics. The dimensions and resolution of the static graphics matched that of the dynamic video.

Basic Computer Network Components

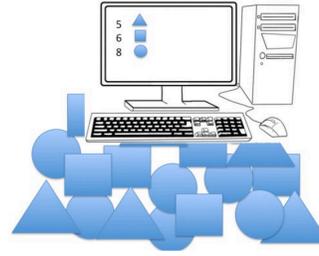


Welcome, in this material we will discuss and explain the basic computer network components.

Next

1 secs

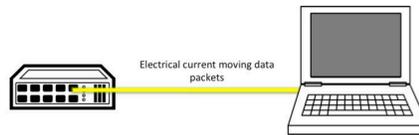
Processing Element



The function of a computer is to organize, interpret and communicate information.

Next

2 secs



A copper cable transmits electrical current containing data packets. The function of a cable is to move data packets from one location to the next.

Next

1 secs

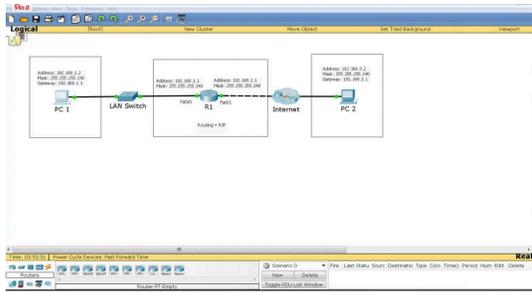
Figure 4. Ex: Static Graphic and Text: Declarative

Procedural Condition

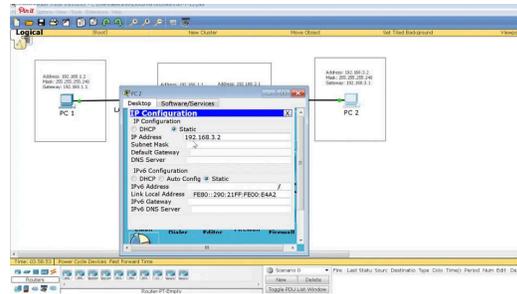
Dynamic Video. The procedural instructional dynamic video consisted of both visual (screencast) and verbal information on how to configure virtual components of a computer network in a specific step-by-step order. The step-by-step procedure consisted of configuring two PC's (entering IP addresses, subnet masks, and routing protocols for each), configuration of a router, and checking connectivity from one PC to another PC. The dynamic video was a recording of a computer screen (screen-cast) accompanied by

narration (male voice) showing and explaining verbally the step-by-step process of setting up a basic computer network in the simulation program *Packet Tracer*. The procedural dynamic video's dimensions were 1024 x 768 dpi and lasted for six minutes and 40 seconds. Participants were allowed to watch the video only one time and could not pause or rewind.

Static Graphics. From the procedural dynamic video, 36 still images of the pertinent visual information were chosen for the static graphics portion of the study. The narration was transcribed into text and matched to each still image. The final set of static graphics contained consistent text located directly under each graphic. The set of static graphics had dimensions the same as the dynamic video. Each static graphic, with matching text, was displayed on a separate webpage. In order to proceed to the next static graphic, a participant could either click a "next" button, or the website would automatically redirect to the next webpage after an allotted amount of time. Again, the amount of time per page was determined by how much time was spent on the same information in the procedural dynamic video plus 20% to account for reading time.



This material will teach you within Packet Tracer how to configure three devices and check end-to-end connectivity after the configuration is complete.



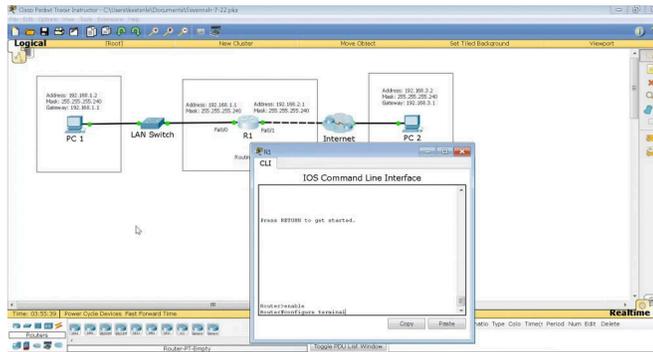
Enter the IP Address of 192.168.3.2

Next

Next

1 sec

12 sec



In order to go into the configuration mode, we have to type: enable and configure terminal.

Next

Figure 5. Ex: Static Graphic and Text: Procedural

Dependent Variables

Declarative test. Using the information from the script of the declarative dynamic video and the SBF method, a 32 item test was created. Test items included questions about the network structures (e.g., “What are two basic physical components needed to make up a computer network?”), behaviors (e.g., “What does a router do with data packets?”), and functions (e.g., “What is the function of a subnet mask?”). The initial 32-item test was administered on a small pool of volunteer participants. An item analysis was conducted and 14 of the 32-items were discarded to maximize test reliability. The 18

remaining items yielded a Cronbach's $\alpha = .70$. Test items were scored on a credit/no credit basis, with a minimum possible score of zero and maximum possible score of 18. Participants had an unlimited amount of time to complete the test.

Procedural test. The procedural test was created by A Cisco Systems Professional. The test contained instructions, and 15 assessment items. The instructions asked each participant to configure two PC's , one router, and check connectivity from one PC to another PC. IP addresses, subnet masks, and routing protocol numbers were provided; participants were not expected to memorize the specific numbers, but were tested on their knowledge of the procedure. The instructions corresponded exactly to the procedure demonstrated in the instructional material. The test was built into *Packet Tracer*, and was automatically scored by the software program, which showed how many of the 15 items were completed. An item analysis was conducted using the participant sample post-test scores and yielded a Cronbach's $\alpha > .80$. There was no partial credit. Participants had an unlimited amount of time to complete the test; however for the pre-test, they were instructed to try and limit their time to 15 minutes. Upon completion of the test, each participant had to save their packet tracer test file to the desktop of the PC on which they were working.

Demographic Survey

Participants were asked to respond to questions regarding their, age, gender, GPA, college major, ethnicity, native language, language fluency, years of computer science experience, and the number of college courses completed in computer science.

End of study questionnaire

A questionnaire was administered asking participants open-ended questions about instructional material preferences and possible improvements to the current instructional material. The questionnaire was administered primarily to provide feedback for Cisco on which type of instructional format the majority of people preferred and how to make instructional material more appealing for their clients.

Website

A website was built using multiple coding languages by two graduate researchers to administer the current study. The website proceeded from page to page, starting with a basic description of the study, and followed by: (a) informed consent page, (b) demographic survey, (c) study instructions, (d) declarative pre-test, (e) break for procedural pre-test, (f) instructional material for each experimental condition page(s), (g) post-test, (h) second instructional material experimental condition page(s), (i) post-test, (j) survey page, and (k) debriefing. All parts of the study were carried out on this website except for the procedural pre and post-tests that took place within the software program *Packet Tracer*.

Procedure

Participants were tested in groups of no more than 24 in a computer lab at the California State University, Chico. The session lasted between 40 – 90 minutes; there was no follow-up session. Each computer was pre-assigned to one of four experimental conditions, set-up by the researcher. On arrival, participants were randomly assigned to the computers and given a specific session id, which was used for saving their *Packet*

Tracer files. Initial verbal instructions were given to participants about the flow of the study and the importance of saving their *Packet Tracer* files onto the desktop with the correct file name. Participants were then instructed to follow the instructions on the computer website and to raise their hand if they had any questions. The first webpage presented participants with an informed consent and asked them to enter their session id. If participants indicated consent to participate, they were presented with a mock scenario about being a computer technician for Cisco in which participants needed to prove their knowledge in order to be hired. They were also presented with the steps of the study and instructions for use of the website. Part one of the procedure was the demographic survey, after which participants went on to part two. Part two was the pre-test for declarative information. After submitting the declarative pre-test, participants moved onto the procedural pre-test. Upon completion of the procedural pre-test, students were exposed to instructional material consistent to one of the four experimental conditions. Immediately after viewing the instructional material, participants proceeded to the post-test corresponding to the instructional material they viewed.

Next, participants were exposed to the second set of instructional material based on the experimental condition to which they were assigned. After exposure, participants immediately proceeded to the second post-test that corresponded to the instructional material they had just viewed. Once the second post-test was completed, they were told they had proved their knowledge and moved onto the end-of-study questionnaire. Finally, participants were debriefed, thanked, and excused.

CHAPTER IV

RESULTS

Declarative Results

In order to assess whether participants learned the declarative information from pre-test to post-test across all conditions a paired samples T-test was conducted revealing a significant increase in post-test scores ($M = 7.40$, $SD = 3.14$) from pre-test scores ($M = 2.08$, $SD = 2.23$), $t(107) = 19.187$, $p < .0005$, $d = 1.85$. See table 1 for pre and post-test means and standard deviations.

Table 2.

Declarative Information Test Scores

	<i>N</i>	Pre-test Scores		Post-test Scores	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Dynamic	53	2.13	2.62	7.44	3.03
<i>Dynamic – Decl. First</i>	28	2.43	3.17	7.14	3.22
<i>Dynamic – Decl. Second</i>	25	1.80	1.83	7.60	2.84
Static	52	2.04	1.81	7.36	3.27
<i>Static – Decl. First</i>	27	2.18	1.94	7.85	3.91
<i>Static – Decl. Second</i>	27	1.89	1.69	7.04	2.49

Note: *N* = number of participants, *M* = Mean, *SD* = Standard Deviation, Decl. First = Declarative First (participants viewed declarative information first), Decl. Second = Declarative Second (participants viewed declarative information second).

Static Graphic vs. Dynamic Video

In order to test our hypothesis, that participants who viewed static visualizations will have higher post-test scores on the declarative information than participants who viewed dynamic visualizations an ANCOVA with the pre-test as the covariate was used. The ANCOVA had two factors visual-medium (static or dynamic) and order (declarative first or declarative second). There was homogeneity of regression slopes as the interaction between pre-test and experimental condition was not significant, $F(3,106) = .228, p = .877$. Standardized residuals for the post-test scores and for the overall model were normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$). There were no outliers in the data, as assessed by no cases with standardized residuals greater than ± 3 standard deviations. There was not homogeneity of variance as assessed by Levene's test of homogeneity of variance ($p = .037$). After adjustments for the pre-test scores, there was no significant effect of order, $F(1,107) = .059, MS_{\text{err}} = 7.794, p = .808$, partial $\eta^2 = .001$, and no significant effect of visual-medium, $F = (1, 107) = .053, MS_{\text{err}} = 7.794, p = .818$ partial $\eta^2 = .001$. Finally, there was no significant interaction between visual-medium and order on post-test scores $F(1,107) = 1.913, p = .170$, partial $\eta^2 = .018$. See figure 1 for a graph of pre and post-test means across all declarative conditions.

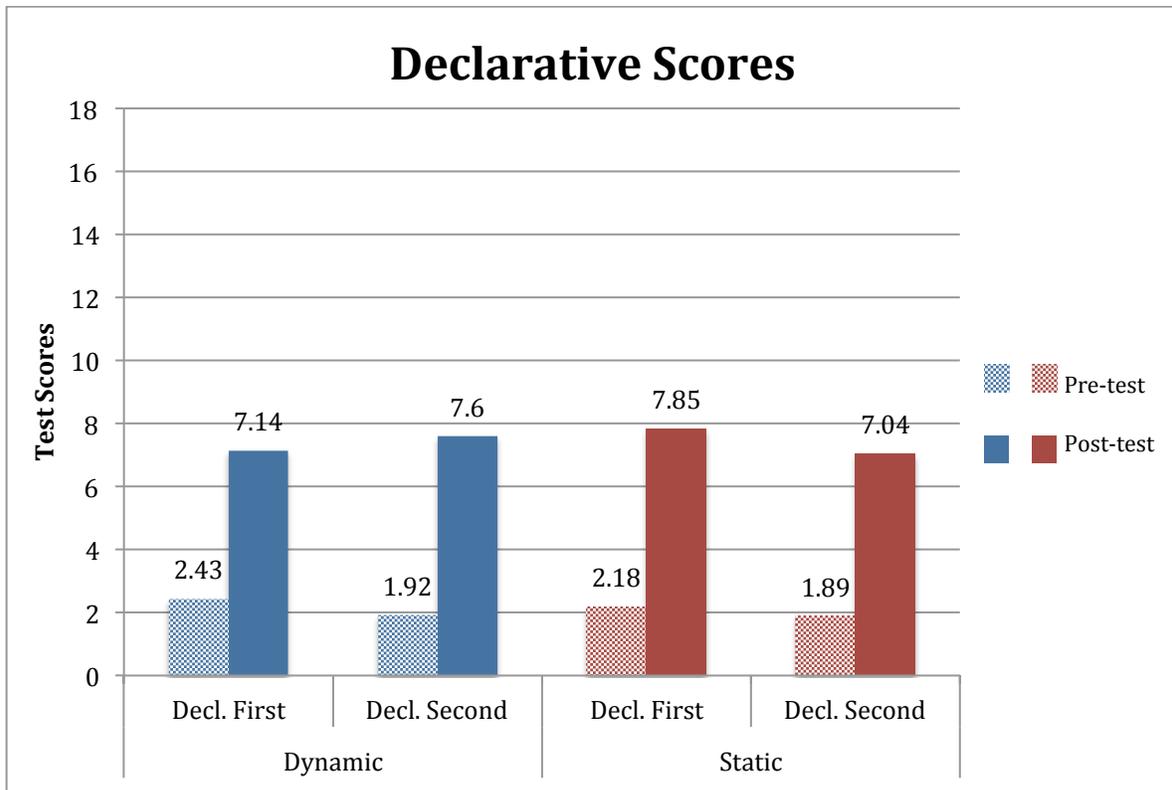


Figure 6. Graph of Declarative Test Scores

Finding neither an effect of order nor an interaction between visual-medium and order, we chose to examine more closely the differences between visual-medium by looking at the portion of our sample that saw declarative information first. We chose to look at differences in visual-medium for this portion of our sample in order to gain insights into our results that did not have the possibility of contamination from exposure to previous instructional material, or possible fatigue effects due to the lengthy run time of the study. To accomplish this, we ran an ANCOVA on the half of our sample who saw declarative information first ($N=53$) with the pre-test scores as the covariate. Differences in mean post-test scores were examined with one factor, visual-medium (static or dynamic). There was homogeneity of variances, as assessed by Levene's test of homogeneity of variance ($p=.123$). There were no outliers in the data, as assessed by no

cases with standardized residuals greater than ± 3 standard deviations. After adjustment for pre-test scores, there was no significant effect of visual-medium on post-test scores for participants who saw declarative information first, $F(1,55) = .979$, $MS_{\text{err}} = 10.329$, $p = .327$, $\text{partial } \eta^2 = .018$, indicating no difference in declarative test scores between participants who saw static graphics and participants who saw dynamic video, see Figure 3.

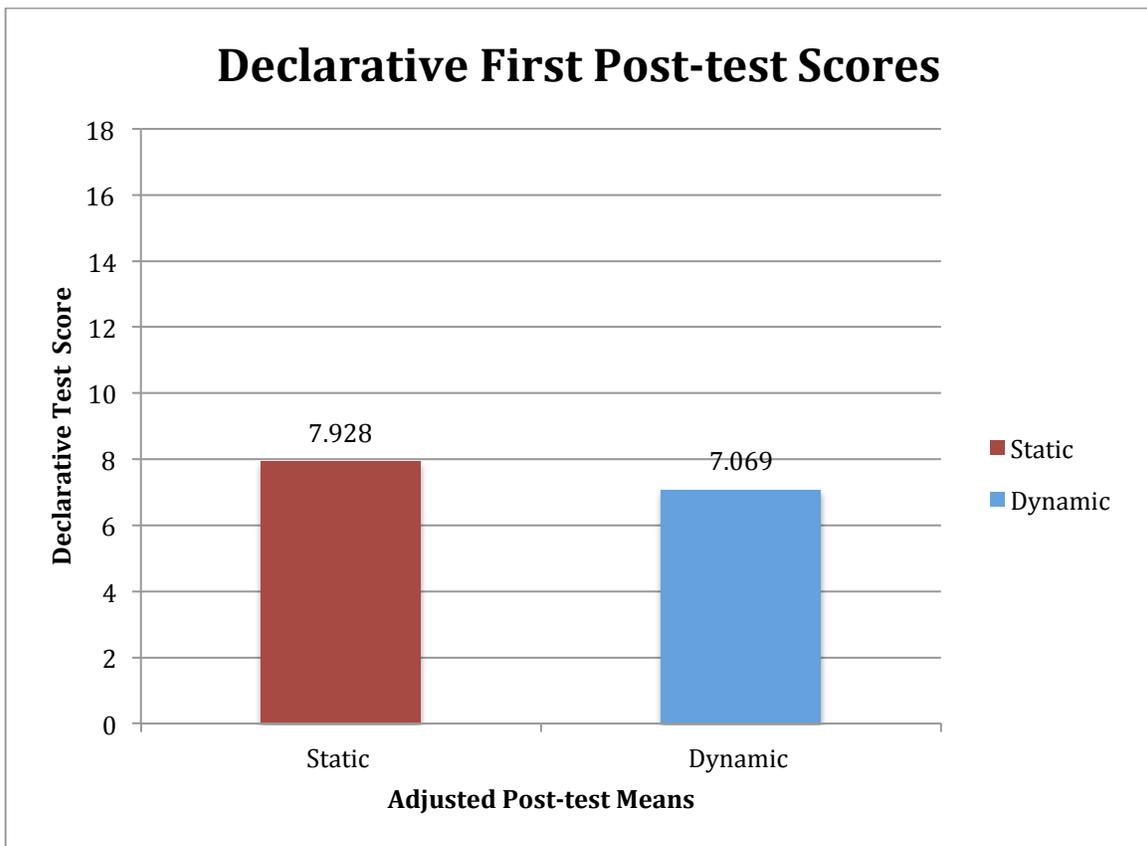


Figure 7. Graph of Declarative First Post-test Scores

Procedural Results

In order to assess whether procedural learning occurred from pre-test to post-test across all conditions, a paired samples T-test was conducted revealing a significant increase in post-test scores ($M=5.60$, $SD=3.17$) from pre-test scores ($M=2.30$, $SD=2.93$), $t(104) = 9.886$, $p < .0005$, $d = .96$ See table 2 for pre and post-test means and standard deviations.

Table 3.

Procedural Information Test Scores

	Pre-test Scores			Post-test Scores	
	<i>N</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Dynamic	53	2.64	3.15	6.23	3.00
<i>Dynamic – Pro. First</i>	26	3.08	2.95	6.65	2.54
<i>Dynamic – Pro. Second</i>	27	2.22	3.33	5.81	3.39
Static	52	1.94	2.67	4.96	3.23
<i>Static – Pro. First</i>	26	1.96	2.96	4.42	2.95
<i>Static – Pro. Second</i>	26	1.92	2.40	5.50	3.45

Note: *N* = number of participants, *M* = Mean, *SD* = Standard Deviation, Pro. First = Procedural First (participants viewed procedural information first), Pro. Second = Procedural Second (participants viewed procedural information second).

Static Graphic vs. Dynamic Video

In order to test our hypothesis that participants who viewed dynamic visualizations would have higher post-test scores on the procedure than participants who viewed static visualizations, an ANCOVA was used, with the pre-test scores as the covariate. The ANCOVA had two factors, visual-medium and order. After controlling

for pre-test scores, there was homogeneity of variances, as assessed by Levene’s test of homogeneity of variance ($p=.734$). Standardized residuals for the post-test scores and for the overall model were normally distributed, as assessed by Shapiro-Wilk’s test ($p > .05$). There were no outliers in the data, as assessed by no cases with standardized residuals greater than ± 3 standard deviations. After adjustment for pre-test scores, there was no significant effect of order, $F(1,105) = 2.13$, $MS_{\text{err}} = 8.551$, $p = .618$, partial $\eta^2 = .002$. However, there was a marginal significant effect of visual-medium (static vs. dynamic), $F(1,105) = 3.073$, $MS_{\text{err}} = 8.551$, $p = .083$, partial $\eta^2 = .030$. There was no significant interaction between visual-medium and order, $F(1,105) = 1.980$, $p = .162$, partial $\eta^2 = .019$. See figure 4 for a graph of pre and post-test means across all procedural conditions.

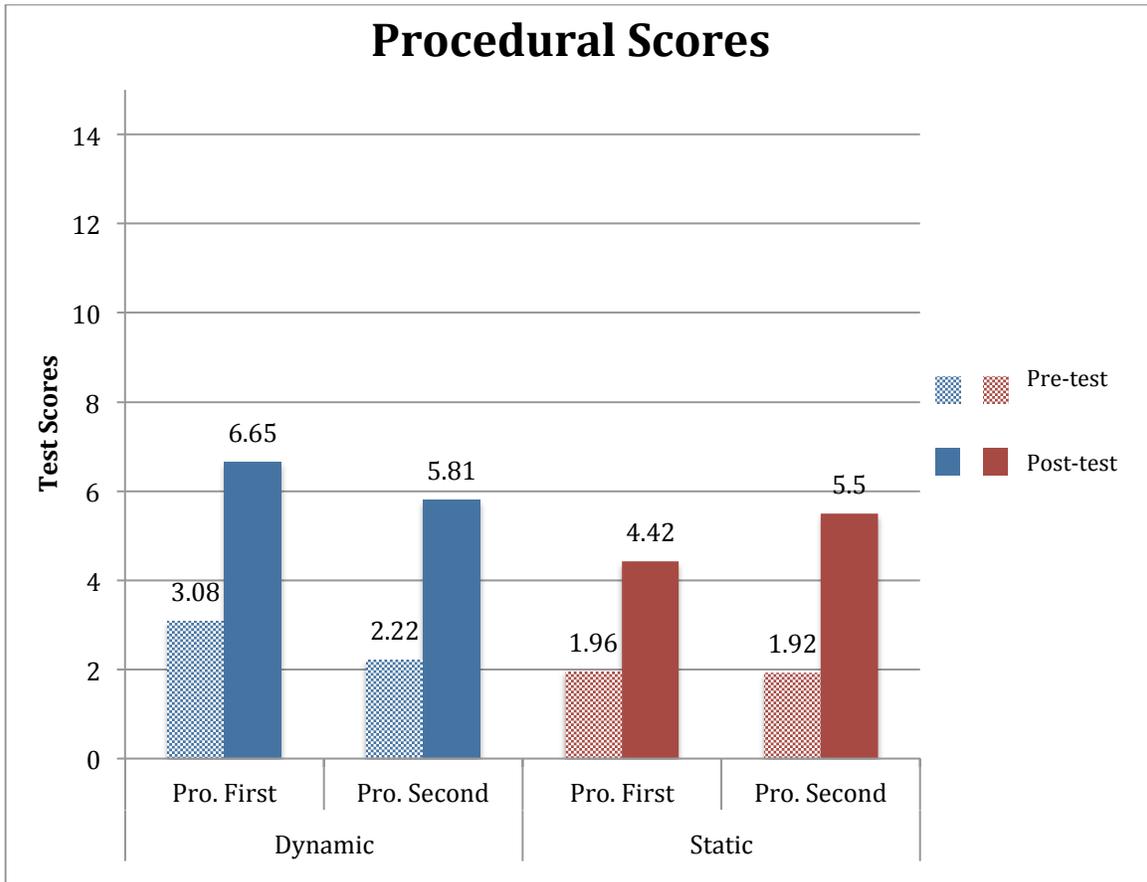


Figure 8. Graph of Procedural Test Scores

Finding neither an effect of order nor an interaction between visual-medium and order, we chose to further examine differences between visual-medium by examining the portion of our sample that saw procedural information first. Again, we chose to look at this portion of our sample in order gain insights into our results that did not have the possibility of contamination from exposure to previous instructional material, or possible fatigue effects due to the lengthy run time of the study. To accomplish this, we ran an ANCOVA on the half of our sample who saw procedural information first ($N=52$) with the pre-test scores as the covariate. Differences in mean post-test scores were examined with one factor, visual-medium (static or dynamic). There was homogeneity of variances, as assessed by Levene's test of homogeneity of variance ($p=.284$). There were no outliers in the data, as assessed by no cases with standardized residuals greater than ± 3 standard deviations. After adjustment for pre-test scores, there was a significant effect of visual-medium, $F(1,52) = 7.982$, $MS_{err} = 7.759$, $p = .007^*$, partial $\eta^2 = .140$ for participants who saw procedural information first. This supports our hypothesis that participants exposed to the dynamic video would have higher average post-test scores on procedural information than participants exposed to static graphics. See Figure 5 for adjusted procedural post-test means.

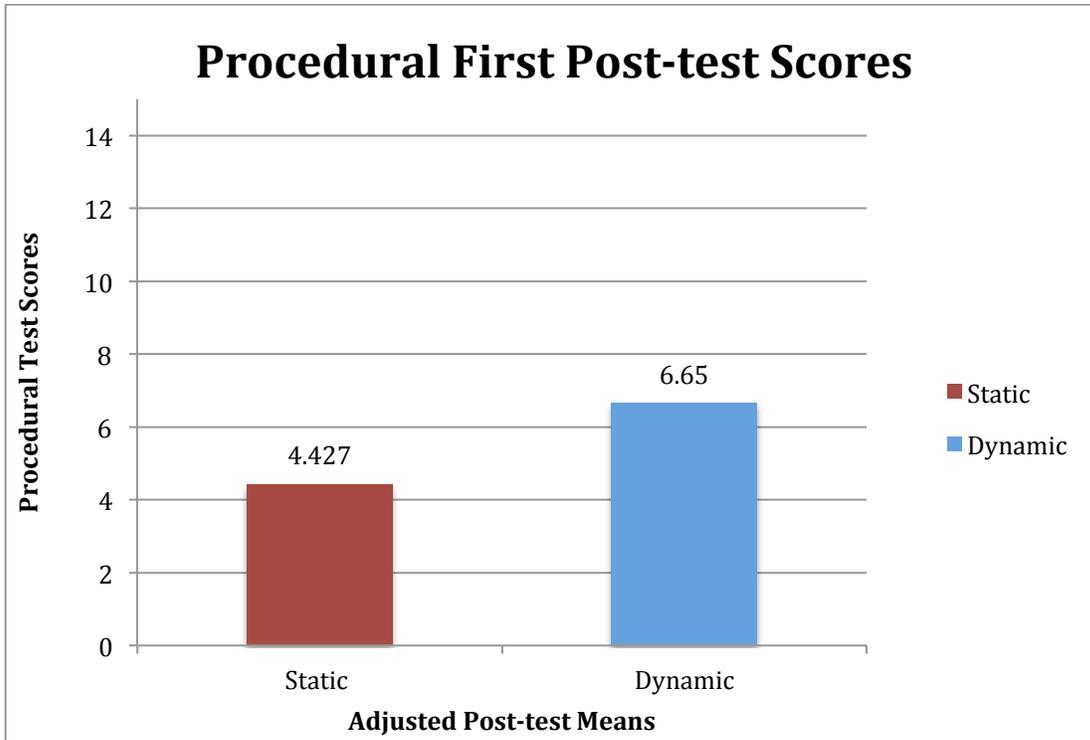


Figure 9. Graph of Procedural First Post-test Scores

CHAPTER V

DISCUSSION

The goal of the present investigation was to determine relative advantages of static versus dynamic visualizations on learning two separate types of information, declarative and procedural. To achieve this goal, participants were exposed to information about computer networks, supported by either static or dynamic visualizations. Participants were exposed to both a declarative set of instructional material and a procedural set of instructional material. Participants were pre-tested to evaluate their initial knowledge level and post-tested to measure knowledge gain immediately after exposure to the instructional material. The present investigation was guided by two hypotheses.

Hypothesis 1 Results and Explanations

Hypothesis 1: We expected to find support for Mayer's (2005) static media hypothesis that states that static visualizations will have higher learning outcomes than dynamic visualizations. We specifically expected support for the static media hypothesis for learning declarative information. Therefore, we predicted that for learning declarative information, static graphics with text (static visualizations) would have higher learning outcomes than a dynamic video with narration (dynamic visualization).

In the present investigation, our results failed to demonstrate reliable support for hypothesis 1. We expected to replicate Mayer's (2005) findings that support the static media hypothesis. Specifically, we expected to find support for the static media

hypothesis for learning declarative information. Our results instead revealed no significant difference between conditions, and more specifically no significant difference between static and dynamic visualizations for learning declarative information first. Consequently, we did not replicate findings from previous research (Mayer, 2005). We offer the following possible explanations:

- (1) It is possible that the dynamicity of the dynamic visualization was neither different nor dynamic enough from the static visualizations. The format of the dynamic visualization was computer-based animated graphics and screencasts of a computer screen. It is possible that the difference between static and dynamic visualizations was not at a high enough level to see differences between the two types of visualizations. It is also possible that dynamic and static visualizations are not binary in their nature. Research up until this point has merely distinguished between dynamic and static visualizations without considering levels of dynamicity in dynamic visualization. This research questions the binary status of dynamic visualizations and posits that perhaps researchers are taking too narrow a view on dynamic visualizations. It is possible that varying levels of dynamicity could alter experimental outcomes. In the future, researchers should investigate different levels of dynamicity on learning outcomes as well as varying formats (screen-cast, realistic video, animation) of dynamic visualizations for teaching the same declarative information.
- (2) Previous literature on visualizations posit that dynamic visualizations may not foster learning as well as static visualizations due to excess extraneous load

and to the rapid pace of dynamic visualizations. Likewise, static visualizations may foster higher learning outcomes than dynamic visualizations because static visualizations allow a learner to be able to re-inspect pertinent information (Mayer, 2005; Hagerty, 2004). We speculate that dynamic visualizations may be worse than static visualizations only when dynamic visualizations are distracting (extraneous load) to the factual information, or the pace of the dynamicity is too fast. In the present investigation, the pace of the dynamic and static visualizations was controlled. Participants viewing static visualizations were offered the same amount of time as participants viewing dynamic visualizations plus 20 percent to account for reading time. The time allotted to view static visualizations may have not been enough time for participants to be able to re-inspect pertinent information, thus reducing the advantage static visualizations may potentially have over dynamic visualizations. It is also possible that our dynamic visualizations offered very little distracting features that would increase extraneous load. Previous studies on dynamic visualizations may have had irrelevant action information, which did not support the factual declarative information on which the students were tested. Our materials were carefully designed in the present investigation using both Mayer's (2009) principles of multimedia and the structure behavior function (SBF) method (Goel, et al., 1996; Lie & Hemelo-Silver 2009). Using both the principles of multimedia and the SBF method, our study may have minimized distracting details from our visualizations, reducing extraneous

load and making the difference between static and dynamic visualizations indiscernible.

- (3) Lastly, Mayer's (2009) text modality principle could help explain why our dynamic visualizations influenced learning outcomes similarly to our static visualizations. The text modality principle states that when animations are to be combined with text, it is preferable that the text be spoken rather than written, in order to avoid split attention. Our dynamic visualizations were complimented by linguistic narration while our static visualizations were complimented by text. Within the static visualization condition the text may have fostered split attention while in the dynamic conditions this did not occur. Future research should investigate the differences between narration and text within static and dynamic visualizations.

Hypothesis 2 Results and Explanations

Hypothesis 2: We expected to find support for Mayer's (2005) dynamic media hypothesis, stating that dynamic visualizations will have higher learning outcomes than static visualizations. We specifically expected support for the dynamic media hypothesis for learning procedural information. Therefore, we predicted that for learning a procedure, a dynamic video with narration (dynamic visualization) would have higher learning outcomes than static graphics with text (static visualization).

Across all four conditions, the results favored dynamic over static visualizations on procedural post-test scores, with no independent influence of order and no mediating effect of order on visual-medium. When we analyzed our results with participants who

saw procedural information first, we found significant differences between dynamic and static visualizations with higher post-test scores for participants who saw the dynamic visualizations. We attribute these findings to the fact that procedural learning outcomes take the form of action, of being able to correctly act out the appropriate steps in a particular order. Learning actions and procedures according to Sweller and Sweller (2006) and Duchaine, et al. (2007) is best supported by imitating other more skilled people. Dynamic visualizations offer viewers an external referent that is most similar to viewing a person acting out the procedure. Specifically, dynamic visualizations offer viewers a complete external referent showing details of specific action information, allowing less room for interpretation than static visualizations. Static visualizations show the beginning and end of action information but fail to display all action information, leaving some interpretation up to the viewer. In the case of procedural learning, we believe that leaving interpretation up to the viewer and not showing a complete model of the action fails to support the viewers' visual representation of the to-be learned information. Our results support that dynamic visualizations are better suited for learning procedural information than static visualizations.

On the other hand, Declarative post-test means across all conditions were very similar. We assume this could be because the dynamic and static visualizations were not different enough from each other or because our dynamic visualizations did not distract from the relevant to-be-learned information and were therefore just as successful as the static visualizations.

Limitations

The current investigation is limited in a number of ways despite our best effort to create a carefully designed and implemented investigation.

First, our participant sample pool limits the generalizability of our study. Our participant sample was comprised of college students recruited from the psychology and computer science departments within a mid-sized University in the western United States. Our sample is younger, less ethnically diverse, and even less academically diverse than the target population. However, there were a high number of computer science students, which is useful for generalizing our results to the domain of computer networking. Our sample pool only consisted of 110 participants, which is not a very large sample for the present investigation.

With regards to the materials of this investigation, we created all new materials based on an analysis of the domain. To the best of our ability, we attempted to vary dynamic and static visualizations, while presenting the to-be learned material in a way that was informationally equivalent. However, we cannot be sure that our dynamic visualizations—especially in the declarative condition—were dynamic enough or different enough from our static visualizations. In subsequent research, it will be essential to make certain that there is enough dynamicity in the dynamic visualization.

Finally, within the present investigation, we also used the computer software program *Packet Tracer*. This software program allowed us to achieve our goal of using a virtual platform for setting up a computer network, but it also posed challenges. First, the software program could not be integrated into the website which did not give us the complete experimental control over when participants were using the program. In some

cases, it was observed that participants manipulated their pre-tests while viewing instructional material. The researchers gave specific instructions not to do this and monitored the 24 computers during the study to the best of their ability. Anyone caught cheating was dropped from the study; however, some participants may have cheated unnoticed.

Practical Implications

The current investigation contributes to the growing body of multimedia research by distinguishing between two types of information to be learned—procedural and declarative. Previous research has investigated differences between static and dynamic visualizations, either for declarative information or for procedural information, with mixed conclusions. In the current study, we chose to differentiate and look at both declarative information and procedural information within the same topic domain. The present study adds to multimedia research finding no significant difference between static and dynamic visualizations for learning declarative information about computer networking. The present study also shows an advantage for dynamic visualizations over static visualizations for learning a computer networking procedure. The procedure in this study was a virtual procedure, which took place within a computer software program *Packet Tracer*. Previous research to our knowledge has only shown simple physical procedures such as how to tie a knot (Schwan & Riempp, 2004) or how to fold paper (Carroll & Wiebe, 2004). The current study adds to the body of research on procedural knowledge by using a procedure acted out on a computer. Today, many tasks and

procedures use a computer; this study demonstrates results that can be extended to learning on a computer.

Primarily, the results of the present investigation demonstrate the importance of differentiating between knowledge types when presenting instructional material. Instructors and anyone presenting information should closely consider what they expect from their learners and what type of information they are presenting to learners. Especially in the case of procedural knowledge, instructors should consider using dynamic visualizations over static visualizations—at least for the type of knowledge and conditions demonstrated here.

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