2014-08-15

The Cerebral Hemodynamics of Cognitive Load: Learning Anatomy with Static and Dynamic Digital Images.

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The Cerebral Hemodynamics of Cognitive Load: Learning Anatomy with Static and Dynamic Digital Images.

by

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A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE

DEGREE OF DOCTOR OF EDUCATION

Graduate Programs in Education

CALGARY, ALBERTA

August, 2014

Abstract

Educational technology research often focuses on the development and implementation of tools for learning. The efficacy of tool development and implementation is regarded as successful if learning outcomes demonstrate an overall improvement. Studies in educational technology also examine the impact or effect of technologies on the learner. The goal of the present study was to determine if cognitive load would be manifested in a measurable physiological response. The present study examined the physiological impact of learning with static and dynamic images by measuring changes in mean cerebral blood velocity (CBV) of the right middle cerebral artery. It was determined that spatial ability has the greatest effect on changes in cerebral blood velocity and learner performance using complex images. Further, this study examined the relationship between perceived mental effort and changes in cerebral blood velocity in high and low spatial ability groups. It was determined that the while the relationships between changes in CBV and high and low spatial ability are weak, the direction of the relationships suggests a possible interaction that warrants further investigation. The findings from the present study show that spatial ability is a variable that impacts cognitive load. However, measuring specific elements of cognitive load is a challenge as they likely occur simultaneously during learning and can be difficult to isolate for investigative purposes.

Acknowledgements

I am indebted to many individuals for their contributions to my study. Dr. Tim Wilson has had the most profound impact on my doctoral journey. He has been a mentor, colleague, and friend. It was through his guidance and encouragement that I was able to persevere and see this journey to completion. I am also grateful for the support and encouragement of my committee members, Dr. Ken Meadows, Dr. Sal Mendaglio, and co-supervisor Dr. Michele Jacobsen. My committee handled working collaboratively in a multidisciplinary setting with professionalism and skill.

I would like to give special thanks to Dr. Kevin Shoemaker for allowing me to use his laboratory and equipment, and to his lab staff for their assistance and guidance during the data collection phase of this study. I am especially thankful for the help provided by Ms. Nicole Coverdale, Ms. Arlene Fleischhauer, and Ms. Carly Barron during my time in the Laboratory for Brain & Heart Health (Shoemaker Lab).

I am grateful for the understanding and kindness of my colleagues, Ms. Dale Shelley and Dr. Peter Flanagan. Their patience, support and encouragement made this process possible. I would especially like to acknowledge Dr. Anita Woods, Dr. Angela Nissen, and Professor Tom Stavraky for their time in helping with understanding physiological concepts that were critical for the present study. I would like to thank Ms. Stacy Miller for her advice and assistance on statistical analysis for the present study. Finally, I am eternally grateful for the support and encouragement given by Dr. John Girvin. He has been an invaluable resource for issues related to neurophysiology and he has been an inspiration to learn more about the complexities of the human brain. I am thankful for his willingness to help and his obvious skill as a surgeon.

To my parents Frank and Linn Loftus, and my brother Paul for their unwavering support and encouragement over many years.

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“As followers of natural science we know nothing of any relation between thoughts and the brain, except as a gross correlation in time and space.”

Sir Charles Scott Sherrington

Man on His Nature (1951)

Chapter One: **Introduction**

1.1 Introduction

The affordances of technology in education have been well documented throughout the academic literature (Dawley & Dede, 2014; Mao, 2014; Ozcinar, 2009b). Much of this research has focused on design aspects, the use of multimedia tools, and the potential benefits for institutions in terms of enrolment and cost savings (Allen & Seaman, 2010, 2011; Bates, 2000; Heylings, 2002). Educational processes that include contemporary technologies are often evaluated to ensure that implementation of the technology does not hinder learning (Garg, Norman, Spero, & Maheshwari, 1999b; Hay et al., 2008; Huwendiek, Muntau, Maler, Tonshoff, & Sostmann, 2008; Ruiz, Mintzer, & Leipzig, 2006). In spite of this line of research, we have rarely examined the impact of technological tools on the learner from a physiological perspective to determine how this impacts the learner's ability to effectively use technology (Lowe, 2004; Whelan, 2007). Much of the educational technology literature has focused primarily on performance measures, excluding any in-depth analysis of the cognitive processing required to effectively use technology (Burns, 2013; Hedberg, 2014; Kalyuga & Sweller, 2005). Technologies that fail to compare favourably with established methods of instruction are often abandoned. There needs to be an exploration of the root cause for the disparity such that new technologies can become effective and ultimately useful for instructional purposes.

The present study is significant in the discipline of educational technology as it attempts to provide a different approach for the evaluation of educational resources and their efficacy for learning. This study has taken a direct approach to evaluating underlying physiological processes supporting learning and cognition. By examining the physiological responses of the brain during learning, some inferences can be made about a learner's ability to the use of technology effectively for learning. Furthermore, by using visual delivery modalities typical of modern educational technology tools, correlations with learner performance and predictions of effectiveness can be made for specific learning tools. Evaluating instructional tools in this regard will provide evidence of efficacy as well as highlight how these tools tend to impact the cognitive processing of learners. Cognitive Load Theory (CLT) will provide a framework for contextualizing the results of this body of research. The approach taken in the current research is counter to one often taken in education where findings from basic science are applied to educational practice (Davis, 2004; Dekker, Lee, Howard-Jones, & Jolles, 2012). Typically instructors are lead to believe their instructional design can target specific regions of the brain to enhance learning (Goswami, 2006; Hardiman, 2012). The approach taken in the present study will provide a basis of physiological evidence for educational theories. Often, educational theories incorporate tangential evidence from basic science and neuroscience research that mars the interpretation or application in a pedagogical sense (Dekker et al., 2012).

Previous research has highlighted the need to evaluate educational tools before their widespread implementation (Hedberg, 2014; Khalil, Paas, Johnson, & Payer, 2005b; Lowe, 2004). The spread of instructional technologies in practice often outpaces any rigorous evaluation for learning. Further, the common modes of evaluation are often limited to comparison studies or case studies that highlight the fact that new tools are at least as good as previous tools or techniques of instruction. Educational research often fails to explain why technologies, or modes of instruction, are not comparable if and when differences exist.

1.2 Definition of Terms

For the present investigation there are many terms and acronyms that will be used throughout this dissertation. Many of them are drawn from cross-disciplinary fields. To help organize the understanding of the content presented within the following definitions will apply:

Static Image - Images that do not show any continuous movement, but only show specific states taken from such a flow of motion (Kühl, Scheiter, Gerjets, & Gemballa, 2011b). Static images are akin to those found in textbooks. Recent studies have used screen captures of dynamic visuals for static images in their testing (Höffler & Schwartz, 2011; Kühl et al., 2011b).

Dynamic Images - Kühl, Scheiter, Gerjets, and Gemballa (2011a) considered dynamic visuals to be animations or videos that are depictions that change continuously over time and represent a continuous flow of motions (e.g. of an object). Lewalter (2003) also defined dynamic visualizations as those that can directly display changes in space over time, either incrementally or continuously.

Extraneous Load – The cognitive load imposed on learners by the design of instruction. High extraneous load requires different activities from learners that are different from the sequences and steps required of the learning task (Kalyuga, 2010). Examples of extraneous load are best illustrated through design examples. For example, when information is separated over distance (e.g. page separation) and time (e.g. sequence of presentation), the integration of information may be more difficult.

Intrinsic Load – This is the cognitive load associated with the internal complexity of the instructional material (Kalyuga, 2010).

Germane Load – This is the load associated with cognitive activities intentionally designed to foster schema acquisition and automation (Kalyuga, 2010; Sweller, 1988a). This is the positive aspect of cognitive load that instruction aims to increase at the detriment of the other two elements.

Transcranial Doppler (TCD) – An ultrasound technology used to measure changes in cerebral blood flow velocity that reflects changes in metabolism due to cerebral activation (Hartje, Ringelstein, Kistinger, Fabianek, & Willmes, 1994). In terms of visual tasks, TCD has shown an increase in blood flow in the middle cerebral artery (MCA) due to increased cognitive demands of complex images (Hartje et al., 1994).

Cerebral Blood Velocity (CBV) – This is a measure of the change in velocity (cm/s) in the middle cerebral artery of the brain. CBV has been found to correlate with cognitive processing (Kelley et al., 1992). Although a velocity, the calibre of conduit arteries, like the MCA, are stable across a wide physiological range (Aaslid, Markwalder, & Nornes, 1982).

Middle Cerebral Artery (MCA) – The artery that supplies roughly 80% of the cerebral cortex with blood (See *Figure 1)* (van der Zwan, Hillen, Tulleken, Dujovny, & Dragovic, 1992). The profusion region supplied by this artery includes areas of the cortex responsible for processing visual information (Kelley et al., 1992; Stroobant, Van Nooten, Van Belleghem, & Vingerhoets, 2005; Stroobant & Vingerhoets, 2000).

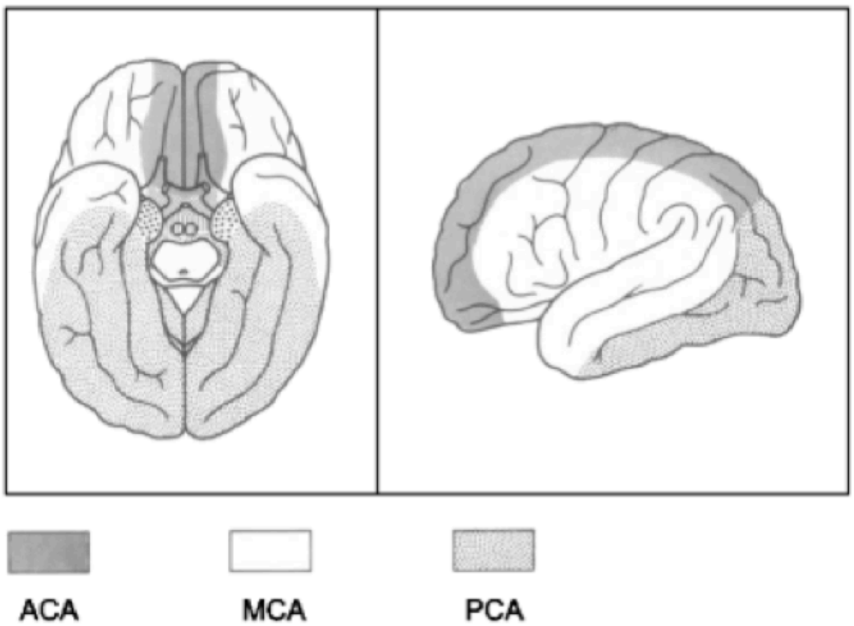

Figure 1 Profusion area of cerebral arteries (Duschek & Schandry, 2003) [1]

End-Tidal CO_2 ($EtCO_2$) – This is the partial pressure or maximal concentration of CO_2 at the end of an exhalation cycle. It is expressed as a percentage of CO_2 or mmHg. This is often used as a correlate during TCD studies since CO_2 affects downstream cerebral blood flow and it is responsive to psychosomatic responses such as anxiety (Wientjes & Grossman, 1994). If $EtCO_2$

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[1] Permission for use granted by Wiley & Sons Publishing

measures between high and low spatial learners are found to be different, this could be reflected in the CBV values. Therefore, changes in CBV could be the result of anxiety or increased heart rate rather than cognitive processing (Aaslid et al., 1982; Kelley et al., 1992; Stroobant et al., 2005; Wientjes & Grossman, 1994).

1.3 The Problem

This section outlines the origins of the problem being investigated in the present study. The rationale for examining the implications of using digital media for learning, the significance and need for examining the impact of digital media will be described based on prior research and current trends in the field of educational technology.

1.3.1 Rationale, Significance, and Need for the study

Nearly two decades ago, Bruer (1997) wrote that, ‘currently, we do not know enough about brain development and neural function to link that understanding directly, in any meaningful, defensible way to instruction and educational practice’ (p.4). Lowe (2004) more recently states that research needs to evaluate the relationship between brain function and instructional practice, and the use of educational technology. In that respect, the bridge is not ‘too far’, to use Bruer’s analogy (1997). The increasing use of technology in instruction, and the addition of tools developed for learning requires a thorough analysis of their impact on student learning and behaviour. Comparison studies, while important, can be dismissive if the results suggest that technological interventions are subpar in comparison to established practices. When discrepancies exist, new technologies may be abandoned prematurely and not evaluated to determine where the deficiencies rest.

Evidence that new evaluation strategies for instructional tools are required can be found within the academic literature.   Manuscripts abound about specific technologies rather than investigations related to pedagogical or instructional practices of said technologies (Becker, 2010; Buchanan, Sainter, & Saunders, 2013; Kazley et al., 2013; Mastrian, McGonigle, Bixler, & Mahan, 2010; Petrova & Chun, 2009; Venkatesh, Croteau, & Rabah, 2014). This disparity highlights the impetus for the present study. That is, the field of educational technology needs to assess the usefulness and the impact of technology, not merely focus on the development of tools. From that perspective, the present study does not focus on one specific technology in practice; rather, the study focuses on the implications of a particular realm of technology (i.e. digital media) on learning in a particular discipline (e.g. anatomy) by studying physiological responses in the brain. The findings presented within this research have ramifications for a broader audience where digital media is used as an instructional tool.

1.3.2 Theoretical framework for the research

The theoretical framework for the present study (See *Figure 2*) attempts to synthesize a wide body of knowledge from an interdisciplinary field of educational technology, psychology, physiology and neuroscience. The challenge is to amalgamate these disciplines into a coherent framework that helps to focus this study. Using the process described by Crotty (1998), the theoretical framework for the present study is presented in diagrammatical form below. A detailed description of the theoretical framework will follow.

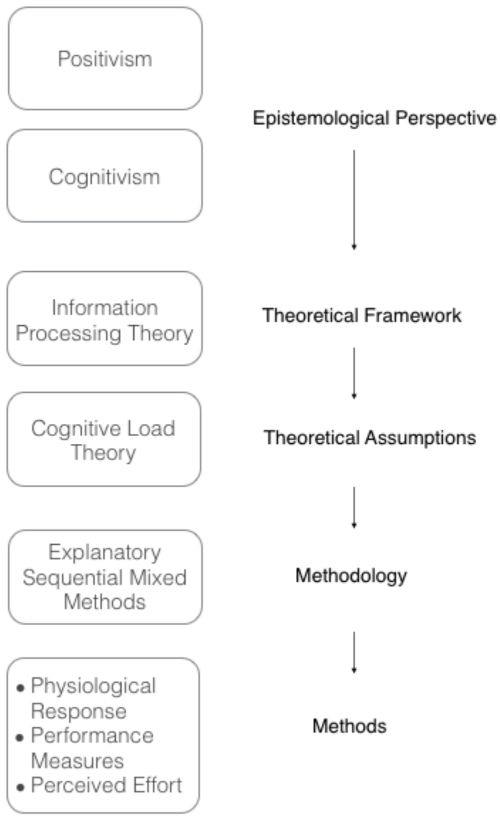


Figure 2. Schematic of Theoretical Framework for Dissertation

This research is based on a positivist approach to understanding the nature of knowledge. The research process conducted within the present investigation contains elements of an experimental approach where objective measures of physiological responses and performance will serve as the data for interpretation and analysis. This approach to understanding learning and the acquisition of knowledge aligns with the cognitivist perspective. Cognitivism is based on the thought processes behind behaviour, using observed behaviours to understand what is occurring in the learner's mind (Walling, 2014). Kivunja (2014) suggests that the cognitivist views learning as the situation where learners think and actively engage in what is required in order to learn. That is, learning requires attention and interaction with the external world. However, learning and ultimately the development of knowledge is an internal process localized within the human brain.

The above epistemological stance provides the lens that will be used to look at the current research problem and make sense of it. The theoretical perspective is a more concrete or detailed view of how the researcher will attempt to verify the development of knowledge or the source of knowledge. For the present study, the theoretical perspective is derived from the Information Processing Theory (IPT), a branch of cognitivism that is the prelude to cognitive load theory (CLT). Theoretical assumptions derived from CLT will be the emphasis of the present study (Ormrod, 1999).

Information Processing Theory (See *Figure 3*) is not a specific theory, rather it is a generic classification given to theoretical perspectives that examine the sequence or execution of cognitive events (Schunk, 2012). Information Processing Theory is concerned with how people attend to events, encode information and relate it to knowledge previously acquired and stored in long-term memory. This relationship is often depicted with diagrams similar to that presented below (*Figure 3*).

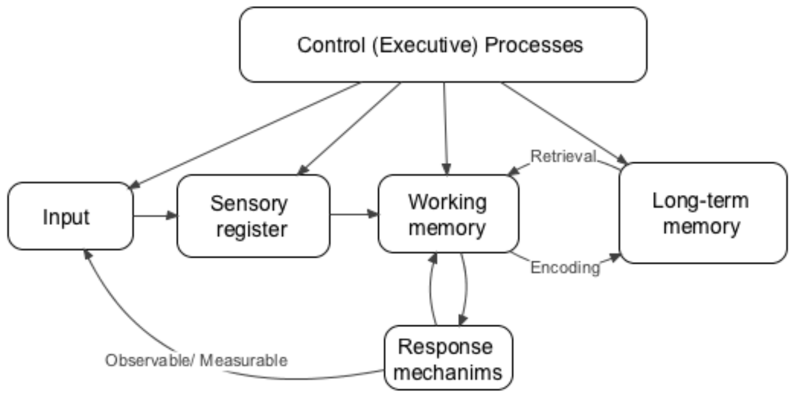


Figure 3. Information Processing Theory Schematic

Information Processing Theory begins with an external stimulus that acts as the input (e.g. visual, audio). This information is reconciled or interpreted in the sensory register. The information that is resolved is held in working memory where it adds to or is compared to information held within long-term memory. Working memory is also the location where the response mechanism (i.e. decisions) acts to interact with the external world. These interactions are the measurable phenomena that provide evidence of learning.

The theoretical assumptions or principles derived from CLT will help to shape the analysis and interpretation of the quantitative data that is obtained in the present study. To enhance the richness of interpretation, field notes or observations during testing procedures were collected. For this reason the methodological approach for the present investigation could be classified as an explanatory sequential mixed methods design. As stated in the foregoing, data collected for analysis will be derived from physiological measures, performance measures, and perceived mental effort or exertion. Comparisons will be made between participants with high and low spatial abilities as this has been shown to have a positive correlation with learning anatomy, and the ability to use technology for learning effectively (Garg, Norman, Eva, Spero, & Sharan, 2002; Nguyen, 2012; Nguyen, Nelson, & Wilson, 2012).

The following sections will explore the origins of cognitive load research. The discussion will begin with the origins of objectivist approaches to studying knowledge, and will finish with the principles of CLT that serve as the focus of the present research. It is important to note that all of these theories assume that the brain is the root of interpretation of information, and therefore knowledge. The challenge of the present research is to determine how this incoming information is reconciled to produce evidence of learning. To date, the intermediary stages of this process have been the source of divergent perspectives of instruction and the use of technology for learning.

1.3.3 Theory Specific to Research Topic

Cognitive Load Theory (CLT) serves as the guiding focus for the present research. The origins of CLT and the primary philosophical tenets associated with it are inextricably linked to Information Processing Theory (IPT) and the biological basis of learning. The theoretical perspective for the current research will explore the assumptions of the biological basis of learning as it serves as the catalyst for CLT. It will become evident that both the biological basis of learning, IPT and CLT view learning and memory as synonyms (Pinel, 1993). Further, the biological basis of learning and CLT focus on the activity within the brain as a means to define how learning occurs. For this reason it is hard to separate the biological basis of learning from the assumptions made by CLT.

1.3.3.1 The Biological Bases of Learning

The biological bases of learning can be followed back to a point in time when humans began questioning and writing about the nature of knowledge, knowing, and being. When Descartes attempted to explain how one knows or how knowledge is acquired, the physical realm, or the brain was discussed as the entity responsible for knowledge and cognition. The present discussion of the biological bases of learning begins with a description of Descartes' notion of the nature of knowledge and cognition. This description serves as a prelude to modern theories that have evolved into the foundation for modern neuroscience, and inevitably cognitive load theory.

1.3.3.1.1 Epistemological Issues

The search for a biological explanation of learning and cognition must begin with an age-old question regarding the reconciliation of the human's 'sense of being' (Anderson, 1997). Consciousness transcends time and space. However, our ability to comprehend this complex dilemma is the result of the orchestration of material substances bound to a space-time continuum (Anderson, 1997; Baruss, 1996). Other disciplines like philosophy and the humanities have attempted to provide evidence that humans are more than mere 'biological machines' (Anderson, 1997). Psychology has attempted to produce a coherent explanation of cognition, consciousness and the nature of knowledge that combines these theories and evidence from a wide and ranging interdisciplinary perspective. Presented here are three perspectives of human consciousness and cognition that will serve as parts of the framework for understanding the holistic theory of the biological bases of learning.

1.3.3.1.2 Descartes' Dualism

The primary tenet of dualism from the Cartesian perspective is the separation of the mind and body. This fundamental principle assumes that there is a non-materialistic entity (i.e. soul) that is responsible for our sense of knowing and free will. The mind (*res cogitans*) and the body (*res extensa*) are completely different entities, and therefore have two distinct (e.g. dual) existences (Flanagan, 1991). These two entities interact through a seemingly symbiotic relationship. The mind is responsible for all mental activities such as decision-making, reflection, and the establishment of goals. The body is responsible for interaction with the external world through movement and manipulation of the physical realm.

Cartesian dualism is presented within this discussion on the biological bases of learning because it serves as a paradox. On one hand the notion that thought processes and cognitive reasoning are somehow removed from the physical or biological entity of the brain is challenging. However, on the other hand this notion highlights an important truth about the present research and all research related to learning. That is, we cannot directly observe learning. Learning is an unobservable and complex phenomenon. What we can observe and measure are the results of learning. As Sherrington (1951) stated, 'as followers of natural science we know nothing of any relation between thoughts and the brain, except as gross correlation in time and space' (p.229). This leaves us with the ability to draw inferences, make correlational statements and assumptions about what is occurring during learning. However, the essence of learning continues to be a mystery, which has resulted in countless theories about the acquisition of knowledge. We know that learning has something to do with the physical entity of the human brain. As will be discussed later, when the brain is affected with aliments or pathologies, certain specific abilities are lost, thus providing evidence that the brain and the physiological processes that control it are the essence of knowledge acquisition and learning (Anderson, 1997; Flanagan, 1991).

In light of the present study, Cartesian dualism offers some appeal. It circumvents the need for complex scientific theories that are difficult to validate or reproduce. Flanagan (1991) suggested that dualism precludes the need for the construction of a scientific theory based on three reasons: (1) if there is no physical dimension of the human mind, then it lacks a fundamental principle of natural sciences; (2) if the human mind is unconstrained by material substances that comprise the body, then dualism again violates modern physical science; and finally (3) if the mind is not testable using tests of inter-subjectivity because the mind is only understood best by the individual, then creating a theory of the mind is a futile exercise (p. 21).

The effect of dualism has been the development of other means to study the relationship between biology and the process and outcomes of learning. As previously mentioned, dualism has challenged not only the premise of where knowledge resides, but how learning or the acquisition of knowledge can be studied – since the process of learning is an unobservable phenomenon. This leads researchers and theorists to use alternative mechanisms for studying learning and knowledge.

1.3.3.1.3 Neurobehavioral Correlative Models

Models that examine the relationship between knowledge acquisition and measurable or observable outcomes are based on correlative relationships. Dualism established the fact that we cannot knowingly observe the essence of learning, while monism holds the position that mind and body are not two ontologically distinct entities. From the monistic perspective, learning and knowledge reside within physical realm of the brain. Neurobehavioral models have generated explanations of how the brain represents and processes experiences by correlating brain states in space and time with sensory phenomena (Anderson, 1997). The objective is to answer questions of 'how' and 'where' changes occur in response to the presentation of sensory information, as a means to understand the nature of knowledge and learning. These models have provided evidence for better understanding brain function and cognitive processing (Esposito et al., 2006; Rypma et al., 2006).

The utility of correlative models is based solely on the intent or purpose of the exploration within the brain. Using data gathered by various imaging and physiological instruments, researchers can answer questions about what happens when an individual thinks about a particular object (Owen et al., 2006; Stroobant, van Nooten, De Bacquer, Van Belleghem, & Vingerhoets, 2008). This line of investigation is similar to that carried out in the research presented in this dissertation. In response to performing a cognitive task, physiological changes will be collected and analyzed to determine the relationship between physiological response and learner performance on outcome tests, which is a basic measure of learning.

As will be discussed later, correlational models have clouded the field of educational research, which has lead to misconceptions of instruction and the use of learning materials (Bruer, 1997; Goswami, 2006). One of the tenets of brain-based learning is that instruction should be designed to 'target' specific brain processes or regions to help foster learning (Bruer, 1997; Davis, 2004; Dekker et al., 2012; Hardiman, 2012). The problem is, no instructional method can specifically isolate individual regions of the brain at the exclusion of others (Dekker et al., 2012; Goswami, 2006; Pasquinelli, 2012). This misconception is the result of attempting to apply neurocognitive research to the field of education (Davis, 2004; Dekker et al., 2012). A more appropriate approach would be to view the brain from a systems perspective. The systems perspective assumes the brain is a complex network of brain regions that work together to produce the phenomenon of learning and memory (Kandel, Schwartz, & Jessell, 2000).

1.3.3.2 Structural – Functional Models

Structural-functional models of human learning place emphasis on the fact that certain regions of the brain are correlated with a psychological phenomenon. Traditionally, function was deducted from altering or removing parts of the brain in animals, as in the case of Lashley (1950) searching for the memory trace or engram. Human studies by Penfield during the surgical treatment of epilepsy helped to highlight the relationship between localized brain region and function (Kolb & Whishaw, 1996).

The emergence of modern imaging technologies and other techniques has enabled theories of learning to develop further, emphasizing the relationship between brain functioning and learning in living humans (Biswal et al., 2010; Schacter, 1992). Through the use of functional brain imaging and mapping, the human brain can be monitored during learning tasks. The conclusions derived from these types of investigations are inherently 'localizationistic' in nature, defining cognitive brain functions as being localized to specific brain areas (Schacter, 1992). Nyberg and McIntosh (2001) suggested that the localization of complex phenomenon such as learning and perception could not be localized to finite or precise areas of the brain (Nyberg & McIntosh, 2001). Complex functions like learning and perception are the result of networks of brain areas, rather than specific or isolated brain areas. These more recent interpretations further emphasize what Lashley (1950) discovered several decades ago. That is, complex phenomena such as memory cannot be isolated to a single structure in the brain. Likewise, learning is also not located within a single region of the brain.

1.4 Information Processing Theory

The three preceding perspectives are important for the present study. First, statements about learning will be based on the result of observable changes in the physical realm of the brain. The phenomenon of learning will be deduced from examining the correlation between test performance and the physiological response to the presentation of visual sensory information. Finally, the location of these physiological changes has focused on a general region of the brain containing the networks of neurons most likely responsible for processing, interpreting and organizing the information required for learning.

The next section will focus on the development of cognitive load theory, starting with the origins in IPT. This background will help to highlight some of the claims that are fundamental tenets of CLT. Information Processing Theory (IPT) is primarily concerned with how information is acquired and stored. It is based on correlational claims garnered from research in memory studies (Baddeley, 2003; Driscoll, 2005; Miller, 1956). As will be discussed in detail, CLT is a further deconstruction of IPT that places emphasis on the acquisition of information through the use of different delivery mechanisms. The tenets of CLT have provided design principles for implementing technological resources for learning. It is the emphasis of delivery that serves as the focus of this dissertation.

Information-processing theory is derived from a Piagetian view of cognitive development that emphasizes the organization of cognitive processes in the human brain, and proposes that the relationship between cognitive architectures, long-term memory, and external cues constitute the learning experience for the learner (Driscoll, 2005). In a strict sense, this view of cognitive development can possibly be considered a branch of constructivism, since, over time and through experience the learner will construct knowledge and build a repertoire of skills and schema to draw upon for decision-making and problem solving (Driscoll, 2005; Ormrod, 1999; Schunk, 2012).

It is evident that IPT is a more primitive and simplistic model of information acquisition, processing and storage. As illustrated in *Figure 3*, IPT makes no distinction between the visual and auditory information in sensory memory. Updated models highlight this distinction more patently into visual and auditory streams of sensory input (Mayer, 2002, 2005, 2010b). Further, working memory in the IPT model has not been deconstructed to specific entities in the same manner as the more recently developed cognitive load theories (Mayer, 2010b; Sweller, 2010). These nuances and similarities highlight the origins of CLT and subsequently newly derived theories with specific applications (i.e. theory of multimedia learning) (Mayer, 2002).

The linear nature of learning, as defined by IPT has resulted in several recommendations believed to enhance learning. Highlighted below (*Table 1*) are the recommendations to enhance learning from the IPT perspective (Driscoll, 2005). There are apparent similarities in the newer CLT model, and these similarities highlight the origin of CLT as a progression from IPT.

Table 1 Some Strategies for Enhancing Encoding into Long-Term Memory

Suggested Strategy	**Corresponding IP Process**
Listen actively and pay attention to cues signalling what is important.	Selective attention[1]
Encode information in more than one-way and more than one mode. Use acronyms and imagery.	Dual code, multiple memory connections[3]
Break down information into manageable parts.	Chunking[2]
Elaborate on new information with examples that are meaningful to you.	Elaboration in encoding[3]

Suggested Strategy	Corresponding IP Process
Read actively. Make the information personal by relating it to your own life.	Elaboration in encoding [3]
Take notes in your own words; don't just write down verbatim.	Elaboration in encoding [3]
Over learn the material. Keep practicing even after you understand content.	Rehearsal, automatically[3]
Review class notes the day you took them.	Forgetting curve[2]
Learn information in a similar way that it needs to be recalled	Encoding specificity[1] (modality effect)

Note: The numbers denoted identify the corresponding aspect of cognitive load theory, 1 corresponds to extraneous cognitive load, 2 corresponds to intrinsic cognitive load, 3 corresponds to germane cognitive load

It is clear from the recommendations presented above that the objective of IPT is to organize information as much as possible for efficient archival into long-term memory. The assumptions underlying each recommendation are that by doing so, the retrieval of this information, and learning, will become more efficient. The notion that learning will become more efficient with better organization has been a difficult assumption to validate (Small et al., 2009a).

1.4.1 Long-Term Memory

Long-term memory is a common aspect shared by IPT and CLT as will be discussed later. Long-term memory is critical for learning as it is the mode by which the learner stores experiences to reflect upon and use for decision making during learning. Before CLT is introduced, a description of long-term memory is provided as it forms the basis of a critical aspect of CLT.

The link between learning and memory is complex (Schunk, 2012). These two terms are often used as synonyms in the academic literature related to education and educational psychology (Driscoll, 2005). Further, learning and memory are often presented as a process that occurs in a continuum of two distinct phases. Kandel, Schwartz and Jessel (2000) provided a description of this distinction by describing learning as, "the process by which we acquire knowledge about the world, while memory is the process by which that knowledge is encoded, stored and later retrieved" (p. 1227). This description of learning and memory has been criticized for being too simplistic as the processes of acquisition and storage are likely to occur simultaneously, rather than in distinct phases (Lynch, 2004).

To help frame the present research, a discussion of the historical origins of memory research is provided. These historical investigations are critical for the present research as they are seminal to the current understanding of learning and memory. Further, these historical research studies help to define the methodology used in the present research in a more concise manner.

1.4.2 Historical Human Memory Research

Karl Lashley was one of the first modern researchers to examine human memory looking for the location in the brain where memories were stored (Kolb & Whishaw, 1996). Lashley referred to this location as the engram, or memory trace (Gustafsson & Wigstrom, 1988). Through his investigations on the memory abilities of rats, Lashley discovered that memory gradually deteriorated and in some cases remained intact despite the gradual removal of cortical structures. From this research, Lashley (1950) concluded:

> It is not possible to demonstrate the isolated localization of a memory trace anywhere within the nervous system. Limited regions may be essential for learning or retention of a particular activity, but within such regions the parts are functionally equivalent. The engram is represented throughout the region. (p. 27)

Following Lashley's attempt to locate the engram in the brain, Canadian psychologist Donald Hebb theorized that memories were likely stored in the brain through assemblies of neurons. These assemblies were collections of neural networks located throughout the brain. These networks were formed through a process known as long-term potentiation (LTP). LTP is based on Hebb's (1949) postulate which states:

> When an axon [the long threadlike part of a nerve cell along which impulses are conducted from the cell body to other cells] of cell A is near enough to excite cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased. (p. 62)

Bliss and Lømo (1970) later confirmed Hebb's LTP postulate by demonstrating the stimulation of a specific nerve pathway in the hippocampus of an anesthetized rat could affect synaptic strength. Bliss and Lømo (1970) found that a brief high-frequency period of electrical activity (called a tetanus) applied (artificially) to a hippocampal pathway increased signal strength of synapses that lasted for longer than 30 minutes. If the tetanus was reapplied the signal strength could last for days or several weeks (Squire & Kandel, 1999). Memories are believed to be stored as a result of stimulus intensity, as well as the number of times the trace is revisited or recalled (Hebb, 1949; Martinez Jr., Barea-Rodriguez, & Derrick, 1998)

In spite of the empirical evidence to support LTP as the potential explanation for memory storage, we cannot accept this as the universal or only mechanism for memory storage in the brain. Long Term Potentiation research has primarily focused on the hippocampus and the pathways associated with this region of the brain (Squire & Kandel, 1999). Further, most LTP studies have been conducted in controlled laboratory environments where conditions make it easier to examine the cellular and molecular mechanisms of memory. Finally, LTP mechanisms have not been shown to occur throughout the brain (Squire & Kandel, 1999). Lashley (1950) alluded to this when he concluded that, 'associative areas are not storehouses for specific memories. They seem to be concerned with modes of organization and with general facilitation or maintenance' (p. 27).

What can be concluded from LTP research is that memories are stored in the brain as a by-product of complex cellular processes. Information that is acquired will stimulate various regions and networks within the brain. The retention of this information is dependent upon the magnitude of the stimulation as well as the number of times this information is revisited or the stimulation is repeated (Martinez Jr. et al., 1998; Squire & Kandel, 1999). These activities within the brain are dependent on the metabolic theory, and are therefore measurable. As, Duschek, et.

al (2008) stated, ‘cognitively induced changes in cerebral perfusion result from the tight coupling between neural activity and brain metabolism’ (p. 81).

1.5 Cognitive Load Theory

Cognitive Load Theory (CLT) is presented following the discussion of IPT since the emphasis of CLT is more directly related to the presentation of learning materials and the effect on learning and memory. Quite simply, CLT is a theoretical construct that proposes how information is acquired and subsequently stored in the brain for learning and retrieval.

The notion of CLT was derived in the late 1970’s by Sweller (1976) and is the subject of much research in the academic literature since that time (Ayres & Paas, 2007; Ayres & van Gog, 2009; Brünken, Plass, & Leutner, 2003; Canes, Di Stasi, Antoli, Alvarez, & Madrid, 2008; Chandler & Sweller, 1991a, 1996; de Jong, 2010; Kalyuga, 2012; Kirschner, 2002; Mayer & Moreno, 2003; Ozcinar, 2009a; Paas, Vanmerrienboer, & Adam, 1994). The outcomes of CLT research have lead to several principles that can be applied to the design of instruction, and the use of technological resources such that the pernicious nature of cognitive load is reduced (Mayer & Moreno, 2003). This has lead to a more specific version of CLT is referred to as the Cognitive Theory of Multimedia Learning (CTML) (Mayer, 2002, 2010b). Each of these will be described in detail below within the context of this research.

In the strictest sense, CLT was never derived or intended to be a learning theory. It was intended to explain the relationship between human cognitive architecture, instructional design, and learning (Moreno & Park, 2010). This section will outline the stages of CLT development and describe the assumptions that serve as the bases for the current understanding of CLT.

1.5.1 *Cognitive Load Elements*

Cognitive Load research began with an attempt to understand the relationship between the types of cognitive processes elicited by different problem-solving tasks and the process of schema acquisition (Moreno & Park, 2010). In this regard, schema acquisition is considered as: i) The building block of skilled performance; (ii) The ability to focus attention directed towards problem resolution and solution; and (iii) The organization of knowledge in long-term memory used to mitigate the burden of heavy cognitive load that interferes with learning (Cooper & Sweller, 1987; Sweller, 1988a).

The initial focus of CLT was on the cognitive demands required for efficient problem-solving (Chandler & Sweller, 1991b). Through the means-ends analysis that took place during the early development of CLT it was determined that problem-solving activities impose a heavy, extraneous cognitive load that interferes with the primary goal of learning (Sweller, 1988a). To help mitigate the impact of 'extraneous cognitive load' research began to investigate the effects of unnecessary cognitive demands imposed by the design of problems (van MerriÎnboer, Schuurman, de Croock, & Paas, 2002). Since careful design of instructional materials and the presentation of problems could minimize superfluous information, and eliminate unnecessary cognitive processing, this aspect of cognitive load was termed *extraneous cognitive load*. The other stages of CLT, intrinsic load and germane load will be described in detail below.

1.5.1.1 Extraneous Cognitive Load

Extraneous cognitive load has been the primary emphasis of research literature in CLT (DeLeeuw & Mayer, 2008b; Mayer, 2010a; Ozcinar, 2009a; van Merrienboer & Sweller, 2010). Extraneous load is often referred to as the cognitive load not necessary for learning, and can be altered through instructional interventions. Extraneous load can be avoided or minimized through better design of learning materials and instruction (de Jong, 2010). For the purposes of the present investigation two traditional cognitive-load effects related to reducing extraneous load are relevant. The first of these is termed the *split-attention effect* (Bidet-Caulet, Mikyska, & Knight, 2010; Chandler & Sweller, 1991b; Mayer & Moreno, 1998), and the second is termed the *redundancy effect* (Chandler & Sweller, 1991b; Kalyuga, Chandler, & Sweller, 1999; Mousavi, Low, & Sweller, 1995; Sweller & Chandler, 1994).

Split-Attention Effect - refers to the situation where the learner's attention is split between multiple sources of visual information that have to be integrated for comprehension. Split attention occurs because individual sources of visual information are unintelligible in isolation. An example of this situation would occur where a complex diagram requires text to explain the diagram. Simultaneous attention to the visual image and text are not possible. The mental integration required for comprehension imposes considerable cognitive load on working memory. In this respect it might be beneficial to think of cognitive load as the mental capacity an individual possesses for comprehension (Halford, Maybery, Ohare, & Grant, 1994; Lusk et al., 2009; Wigboldus, Sherman, Franzese, & van Knippenberg, 2004). Chandler and Sweller (1991) discovered that extraneous load could be mitigated if separated sources of information in the visual modality were integrated. Mayer (1997a) later confirmed these findings and termed this the *spatial contiguity effect*.

In terms of the present investigation, cues within images alter their complexity potentially leading to a split-attention-like effect. The use of multimedia may serve to increase depth cues and even enable motion of images. These effects alone may distract from the intended purpose of the image, rendering it difficult for learning through presumed increases in extraneous cognitive load (Brenton et al., 2007; Garg et al., 2002; John, 2007; Meijer & van den Broek, 2010). The mechanism by which learning is stymied through split-attention effect occurs because the learner must make unnecessary decisions about where to attend and focus their efforts for comprehension. Simple design strategies such as incorporating information into well-organized visuals will help to minimize this dilemma for the learner. Recommendations to minimize extraneous load of complex images may include the ability for the learner to select between dynamic views such as animations, or static views such as a series of perspectives (Garg, Norman, Spero, & Taylor, 1999a).

Redundancy Effect – Similarly, the redundancy effect limits learning through the distraction of duplicating relevant and meaningful information (Mayer & Moreno, 2010b). Much of the work on reducing redundancy explored the use of text and narration, adhering to the premise of the dual channel principle that proposes information should be presented as not to overload one channel (e.g. audio or visual) at a time (Mousavi et al., 1995). However, presenting the same information in more than one form simultaneously still distracts the learner, and affects the ability for information to pass through working-memory into long-term memory (Mayer & Moreno, 2010b). In complex images the addition of multiple views and visual cues conveying depth could prove to be a distraction for efficient learning. The exact reason why this occurs is still unknown and will hopefully be better understood through the present research. To date one hypothesis is that 3D objects are represented in the brain as key 2D viewpoints of the object (Garg et al., 1999a). Thus, the intermediate views given in a dynamic model are deemed to be redundant and impede the ability of the brain to effectively encode this information into long-term memory. The assumption or hypothesis is that the brain has the ability to mentally rotate these images without external cues provided from a model (Brenton et al., 2007; Garg et al., 1999a; Shepard & Metzler, 1971).

As described above, extraneous load is concerned with the delivery of information such that the learner has the ability to comprehend what is being presented. Cognitive Load Theory contends that the excesses of extraneous information is limited by processing capacity, and ultimately transfer of information into long-term memory. This of course, is only one aspect that needs to be considered when using technological tools for learning. The other elements that contribute to our capacity are presented below.

1.5.1.2 Intrinsic Cognitive Load

Unlike extraneous cognitive load described above, intrinsic cognitive load is relatively fixed. Intrinsic cognitive load is imposed by the basic characteristics of information (Sweller & Chandler, 1994). That is, intrinsic cognitive load is concerned primarily with the inherent level of difficulty of content. In this regard, some material is always going to be difficult to comprehend and thus will induce higher cognitive load requiring greater mental effort for comprehension.

In an attempt to help minimize the affects of intrinsic load, Chandler and Sweller (1994) proposed a way to estimate intrinsic load by ‘counting the number of elements that must be considered simultaneously in order to learn a particular procedure’ (Sweller & Chandler, 1994). The term ‘procedure’ appears to be a remnant of the problem-solving origins of CLT. Furthermore, the emphasis on the number of elements is reminiscent of earlier studies on memory; where it was determined humans have a limited ability or capacity for recall of information (Miller, 1956). In the context of multimedia learning, as will be discussed later, and for the present study ‘procedure’ will be broadened to describe various additional elements presented at once. An analogy for intrinsic load for the present study would be the field of clinical anatomy. In the context of clinical anatomy, the learner must be able to identify structures, as well as placement within the body. This relies on prior knowledge and the ability to use external cues for appropriate placement (Petersson, Sinkvist, Wang, & Smedby, 2009; Stull, 2009). Further, identification of the structure requires an understanding of the unique vocabulary used in anatomy, adding to the complexity.

To help minimize the intrinsic load burden on cognitive resources, the most predominate strategy for instruction has been ‘chunking’ content into manageable size for the learner. This method is inextricably linked to the principle of counting elements described above. However, there is a limit to how much content can be ‘chunked’ or grouped without jeopardizing the integrity of the content. As described in the foregoing, learning clinical anatomy requires a certain level of external context for full appreciation. Chunking in this situation might add to the complexity of the content by omitting necessary information such as orientation cues and landmarks.

Cognitive load theory is based on an additive principle. This is the belief that each aspect of cognitive load does not work in isolation of another, and that there is a total amount of cognitive resources available for processing information (See *Figure 4*). Sweller (1993a) commented on the ‘additivity hypothesis’ and stated:

> When people are faced with new material, the cognitive load imposed by that material would consist of the intrinsic cognitive load due to element interactivity and extraneous cognitive load determined by the instructional design used. If the total cognitive load is excessive, learning and problem solving will be inhibited. (Sweller, 1993a)

The additivity hypothesis was significant for the development of CLT as an applied theory. It established two fundamental assumptions. First, extraneous load is the only load that can be reduced through effective instructional design. Second, the role of extraneous load is limited by the quantity of intrinsic load placed on the learner. That is, if intrinsic load is low, higher extraneous load might not affect the learner insofar that it does not exceed a critical level of cognitive load demands placed on the learner (Moreno & Park, 2010).

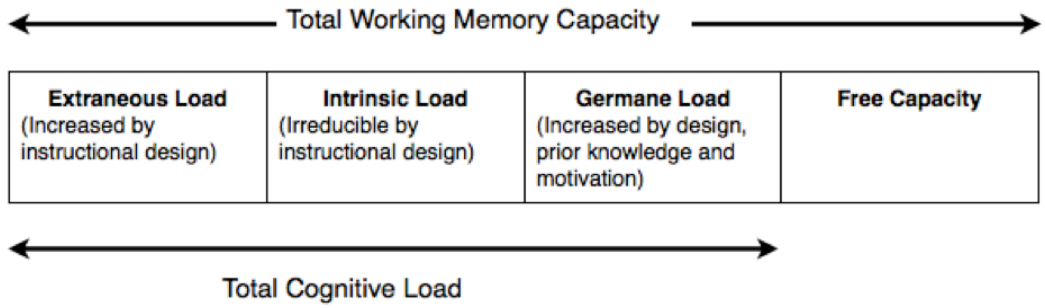


Figure 4. Components of Cognitive Resources for Processing

The ideal learning conditions according to CLT are those where more effort and cognitive resources are available for germane processing. This is accomplished through management of extraneous and intrinsic loads.

1.5.1.3 Germane Cognitive Load

The final element of CLT to be added was germane load. Unlike the previous two elements of CLT, germane load has a positive relationship with learning. Germane load, or generative processing, is the portion of learning in which the learner engages in deeper cognitive processing than attention alone such as mentally organizing material and relating it to prior knowledge. This phase of learning is dependent upon motivation, as well as prompts and support from the learning materials (DeLeeuw & Mayer, 2008b; Nguyen, 2012). Germane load is based on the premise that by reducing extraneous load and intrinsic load, learners will be able to use a bulk of their cognitive resources for the purposes of schema acquisition and automation (Sweller, 2006). Schema acquisition and automation are described as processes that help to reduce the burden on working memory resources through the categorization of similar information presented to different sensory channels (e.g. verbal and visual channels) (Schnotz & Kurschner, 2007). Baddeley (2003) suggests that working memory consists of a phonological loop that is responsible for processing and storing phonological information (e.g. sound of language), and a visuo-spatial sketchpad that is responsible for visual and spatial information. Working memory is intended to prevent the decay of information before it can be encoded or stored into long-term memory (Baddeley, 2003). Working memory is controlled by a central executive that is responsible for directing attention towards relevant information, while filtering irrelevant or extraneous information (Baddeley, 2003). As a result, it has been suggested that instructional design should focus on using cues and prompts to increase the use of working memory resources devoted to intrinsic cognitive load, which would inevitably enhance germane cognitive load (Sweller, 2010). This assumption was the basis of several articles found in the academic literature (Mayer & Moreno, 2003; Ozcinar, 2009a; Sweller, van Merrienboer, & Paas, 1998; van Gog, Kester, Nievelstein, Giesbers, & Paas, 2009; van Merrienboer & Sluijsmans, 2009; van Merrienboer & Sweller, 2010).

The preceding three elements have served as the theoretical framework for CLT. Theories that are derived from CLT use common assumptions and terminology. This is highlighted in the following discussion on multimedia learning. In this section the application of CLT is applied to the design and diffusion of multimedia as a delivery mechanism for learning (Mayer, 1997b; Mayer, 2002, 2005; Mayer & Johnson, 2008). This theory has become even more granular by specifying the use of CLT and multimedia within specific disciplines like medical education (Mayer, 2010b).

1.6 Cognitive Theory of Multimedia Learning

In book III of *The Republic*, Plato argued against the use of written forms of instruction suggesting that it would change the learning experience from that which had traditionally been oral, to one based on text (Plato, 1984). This example serves as an anecdote for the adoption of any new technology for learning. There will always be some reluctance for the implementation of innovations that may have unknown consequences on learning (Ely, 1999; Rogers, 2010; Surry & Farquhar, 1997).

Cognitive Load Theory has provided a framework for the implementation and design of technology. Over the past two decades more focused research on the effective use of multimedia resources for learning has been reported in the academic literature (Dubois & Vial, 2000; Kalyuga et al., 1999; Kalyuga, Chandler, & Sweller, 2000; Mayer, 1997a, 2002; Mayer & Moreno, 2003; Moreno & Mayer, 1999; Moreno & Valdez, 2005; Rummer, Schweppe, Scheiter, & Gerjets, 2008; Seufert, Schutze, & Brunken, 2009; Tabbers, Martens, & van Merrienboer, 2004; Van Gerven, Paas, Van Merrienboer, Hendriks, & Schmidt, 2003; Whelan, 2007; Zheng, McAlack, Wilmes, Kohler-Evans, & Williamson, 2009; Zheng, Yang, Garcia, & McCadden, 2008). The result of this line of research has been the development of implementation principles that are an extension of CLT.

Newer theories, such as Mayer's Cognitive Theory of Multimedia Learning (CTML) (Mayer, 2002, 2005) can be thought of as derivatives of IPT and ultimately CLT. Similarities in structure and terminology suggest a common ancestry (See *Figure 3* and *Figure 5*). In both representations information passes through sensory processing towards working memory, and ultimately through to long-term memory. The newer model proposed by Mayer (2005) places greater emphasis on the learner and their ability to reconcile information from different information sources at one time.

Mayer (2005) defined multimedia as the presentation of words (e.g. spoken or printed) and pictures (e.g. illustrations, photos, animations or video). The emphasis for Mayer is on the learner rather than the delivery of media. The types of multimedia resources described by Mayer (2005) are broad and ranging. This may be intentional as it is difficult to establish a standard or baseline for limiting the amount of media resources used in instruction. Rather than focusing on the amount of media used, CTML proposes principles based on focused attention and modality, which will be addressed below.

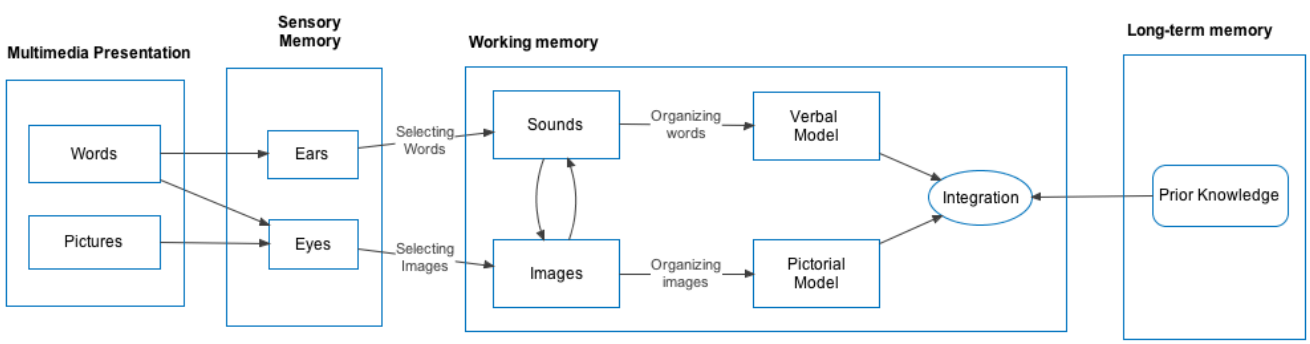


Figure 5. Mayer's (2010) Cognitive Theory of Multimedia Learning

The cognitive theory of multimedia learning is based on three research supported principles from cognitive science: i) *Dual Channel Principle* – States that learners have separate channels for processing auditory and visual information; (ii) *Limited Capacity Principle* – States that learners can only process a few elements in each channel at any one time, and; (iii) *Active Processing Principle* – That proposes meaningful learning occurs when learners are actively engaged in cognitive processing during learning. The cognitive theory of multimedia learning includes attention to relevant information, mentally organizing content into meaningful segments, and comparison and resolution with prior knowledge retrieved from long-term memory (Mayer, 2010b).

The above theory deals with specific cognitive processes as they are related to the use of multimedia tools. Mayer (2010) highlights five main types of cognitive processes. These processes are identified as: i) *Selecting words* – attending to important spoken words; (ii) *Selecting images* – attending to incoming printed words and pictures; (iii) *Organizing words* – mentally rearranging words into a coherent cognitive representations; (iv) *Organizing images* – mentally rearranging the images into a coherent cognitive representation; and (v) *Integration* – mentally incorporating the verbal and pictorial models with one another, as well as comparing these models with relevant prior knowledge in long-term memory.

Mayer's emphasis on the above five cognitive processes is important. However, realistically these processes are not discrete functions in discrete locations as Mayer implies in the separation shown in *Figure 5*. Examples of integrative processing comes from cognitive neuroscience research, it has a long history of illustrating the activation of language centers in the brain when learners are presented with a picture or text (Mellet et al., 1996; Thomason et al., 2009). Similarly, visual centers in the brain are often active when verbal instructions or words are presented in an auditory form (Mellet et al., 1996). These findings suggest that the five processes identified by Mayer are connected and often overlap.

1.7 Summary of Theoretical Perspective

The discussion on the theoretical perspective highlighted the origins of CLT as a derivative and dynamic theory stemming from IPT. As more technologies are included in the instructional toolkit, CLT and the multimedia theory of learning will provide a good theoretical foundation to study the impact of technology on learning, as well as offer principles for prudent use of technology for instruction. This dissertation provides another approach for studying the impact of technology on learning, focusing on the physiological changes in the learner. The theories presented in the foregoing will help the interpretation of the results obtained.

1.8 Statement of the problem to be investigated

The problem that this research seeks to resolve is that of evaluating technological resources used in education. Using physiological measures underpinning cognitive processing and correlating this with learner performance and perceived effort, the goal is to examine the impact of using digital media on the learner and learning outcomes, such that the results will be able to provide recommendations for the use of multimedia resources for learning. Education has adopted many theories and principles from neuroscience research that has no direct application to practice. This is done due to a lack of understanding of the research literature, an over zealous need to incorporate neuroscience research into education, and a broad interpretation of learning (Davis, 2004; Dekker et al., 2012; Goswami, 2006).

In an attempt to amalgamate understandings from physiology, education, and cognitive psychology, this dissertation explores the relationship between physiological measures, test performance and perceived mental effort. The findings from this research will add to the understanding of how technology impacts the learner and what this translates to in terms of performance. The goal is to provide evidence that a relationship between physiological variables and performance can used to add to the methods researchers employ for evaluating the impact of educational tools on the learner.

1.9 Hypotheses, theories, or research questions to be investigated

1.9.1 Hypotheses

The hypotheses proposed for the present research are derived from previous research results found in the academic literature. The assumptions for these hypotheses originate in both the physiological literature and educational technology literature. The term ‘assumption’ is used since this research is fairly novel in that it has not been explored from an educational technology perspective.

Earlier research has demonstrated that individuals with superior mental rotations ability, or spatial ability will outperform individuals with lower spatial ability on anatomy learning tasks (Garg et al., 1999a; Meijer & van den Broek, 2010; Nguyen et al., 2012). The changes in mean cerebral blood velocity in high spatial ability learners and low spatial ability learners has not been compared. It is hypothesized that learners with higher spatial ability will show a decrease or reduction in mean cerebral blood velocity in the right middle cerebral artery compared to their low spatial ability counterparts. The maintenance of basal cerebral activity, and the commensurate cerebral blood flow, is believed to be indicative of increased efficiency and better performance as previously speculated by other authors (Garg et al., 1999a; Meijer & van den Broek, 2010; Nguyen et al., 2012).

In concert with the first hypothesis, it is predicted that the physiological measures of percent changes in mean cerebral blood velocity and the psychological measures of perceived mental effort will be positively correlated. Mental effort has been typically used as a measure of cognitive load (DeLeeuw & Mayer, 2008a; Paas, Tuovinen, Tabbers, & Van Gerven, 2003; Paas et al., 1994). The relationship between perceived mental effort and physiological changes, such as mean cerebral blood velocity has not been realized to date. The second hypothesis for the present research is that mental effort will demonstrate a positive correlation with changes in mean cerebral blood velocity. That is, as effort increases, so too will cerebral blood velocity. The relationship between blood velocity and cognitive processing has been reported in the academic literature (Kelley et al., 1992; Stroobant & Vingerhoets, 2000).

Finally, the last hypothesis pertains to the types of images that are used for learning. Mayer (2002) defined multimedia in relatively simple terms, suggesting that it was the presentation of material using both words and pictures. The current research may apply a more complex definition that includes videos, audio and text (Lowe, 2000, 2004). Therefore, it is anticipated that images that provide greater fidelity and depth cues (dynamic images) will be better for learning, especially in a discipline like anatomy where this information is critical to understanding spatial relationships. Static images, on the other hand require the learner to integrate more of the information internally than is provided in a dynamic image (Nguyen, 2012). Again these results reflect changes in the demand for blood in the brain, essentially neuronal metabolism and are thus related to performance on learning tasks in both high and low spatial ability learners.

1.10 Research Questions

The present research is predicated on many of the theoretical assumptions derived from CLT. As mentioned in the foregoing, this is a prevalent construct in educational psychology and has been used as a design principle for implementing technology in instruction (Averns, Maraschiello, van Melle, & Day, 2009; Bunch & Lloyd, 2006; Chandler & Sweller, 1991b, 1992; de Jong, 2010; Dubois & Vial, 2000; Huwendiek et al., 2008; Mayer, 2008; Ozcinar, 2009b; Yeung, Genaidy, Deddens, & Leung, 2003). This research will provide physiological evidence that answers some of the unknown aspects of CLT. The questions that will be addressed within this investigation are as follows:

1. Can physiological measures such as mean cerebral blood velocity be used as predictors of mental effort when compared to subjective rating scales typically used in CLT research? (Brünken et al., 2003; Kalyuga & Sweller, 2004; Paas et al., 1994).

2. Do measures such as mean cerebral blood velocity support the notion that increased performance is proportional to increase cognitive efficiency (Rypma et al., 2006)? That is, will learners who perform better have lower mean cerebral blood velocity compared to individuals who perform less effectively? (Esposito et al., 2009; Esposito et al., 2006; Kim, Glahn, Nuechterlein, & Cannon, 2004; McIntosh et al., 1999; Raichle, 2001a).

3. Do learners who are more spatially able show differences in cognitive processing, as measured by TCD compared to their lower spatial ability counterparts? (Meijer & van den Broek, 2010; Nguyen, 2012)

4. Can image type; static or dynamic images, impact the cognitive processing of the learner such that these tools are ineffective for learning? How does spatial ability correlate with the measures of cognitive processing (e.g. mean cerebral blood velocity) and test performance?

The above research questions aim to determine if image type has an impact on learning, and if effective use of complex images requires increased spatial ability. Further, the means by which this will be measured should offer another method for evaluating the impact of technology on the learner. The ultimate goal would be to identify the strength and direction of these relationships and determine if interventions to make these tools effective for all learners is required. Previous research findings suggest that additional training for low spatial ability learners may be required for effective use of complex images, especially in visually dominate disciplines like anatomy (Averns et al., 2009; Lowe, 2000, 2004; Meijer & van den Broek, 2010; Nguyen, 2012)

1.11 Summary

The preceding section highlighted the complexity of the present investigation. This is an interdisciplinary study that relies on theories and evidence from psychology, physiology, neurology and education. This study attempts to focus on one overarching theory (CLT), while minimizing the overwhelming number of variables to determine the extent of the affect of digital media on learning. The current study focuses specifically on one channel in the cognitive architecture: the visual stream. This was done to simplify the potential for confounding variables that may influence the outcome of this research.

Chapter Two: **Literature Review**

2.1 Introduction

The primary focus of the present investigation is to examine the effective use of images for learning. It has been demonstrated that complex images like dynamic images, are more effective as a learning tool for individuals who have high spatial ability, and can mentally manipulate the information that is presented (Garg et al., 1999b; Hoffler & Leutner, 2007; Lowe, 1999; Meijer & van den Broek, 2010; Nguyen, 2012; Nguyen et al., 2012; Surry & Farquhar, 1997). Ploetzner and Lowe (2004) defined *dynamic images* as visualizations that can directly display changes in space over time, either incrementally or continuously. This is in contrast to *static images* that do not change in time and space (Hoffler & Leutner, 2007). Further, learning will be defined as the combined process of information acquisition and storage. This definition fits with both IPT and CLT models, and was previously described by Kandel et al. (2000).

The preceding chapter outlined the origins of Cognitive Load Theory (CLT) (Sweller & Chandler, 1991; Valcke, 2002). It was suggested that CLT was a derivative of Information Processing Theory (IPT) (Driscoll, 2005; Schunk, 2012). Also, it was suggested that CLT has been further developed into the Cognitive Theory of Multimedia Learning (CTML) (Mayer, 2002, 2005; Mayer & Moreno, 2002, 2003). This literature review will focus on CLT as it relates to the present investigation. Specifically, it will provide an overview of prior research that explores the use of images for learning, emphasizing different types of images - static and dynamic. The review will also examine prior research that has highlighted the relationship between brain activity and visual learning. Cognate research literature, such as brain-based learning, will also be presented as it pertains to the present investigation. While this may appear to widen the scope of this literature review, cognate research in the area of brain-based learning has had an impact on the educational literature. It also serves as a prelude to the discussion on the issues or misconceptions found within the educational research literature (Dekker et al., 2012; Goswami, 2006).

2.2 Defining Learning from a Cognitive Load Theory Perspective

Cognitive Load Research literature does not provide a universal definition of learning in explicit terms. Cognitive Load Theory literature is predicated on the assumptions from a cognitivist perspective. That is, learning is the result of processes occurring within the brain (Driscoll, 2005; Ormrod, 1999; Schunk, 2012). This notion was emphasized when Mayer (1995) suggested: “Humans are processors of information. The mind is an information-processing system. Cognition is a series of mental processes. Learning is the acquisition of mental representations’ (p. 154). This description of learning is akin to that provided above by Kandel et al. (2000) where learning was described as a sequential process of information acquisition and storage. It is from these conceptualizations of learning that CLT is derived. This description of learning is often highlighted in the CLT and IPT literature through commonly used schematics (See *Figures 3 & 5, Chapter 1*) that emphasize the sequence of information acquisition towards the inevitable destination of long-term memory. In this respect, CLT highlights the importance of intermediary steps along this pathway that emphasize information delivery, organization (schema building) and eventual storage into long-term memory.

Cognitive Load Theory has often been described as a psychological construct that serves to outline effective instructional procedures and techniques that are aimed at the acquisition and organization of schematic information ((Moreno & Park, 2010; Schunk, 2012). As Moreno and Park (2010) suggested, 'a psychological construct is an attribute or skill that occurs in the human brain' (p. 9). Therefore CLT, as has been discussed, is based on assumptions about the cognitive architectures within the brain that are responsible for this acquisition and storage of information (Reed, 2006; Sweller, 2003; Sweller et al., 1998). The next section will discuss the impact cognitive load has on learning as defined in the foregoing.

2.3 Cognitive Load Effects on Learning

Previous CLT research has deconstructed cognitive load into three elements that contribute to the total cognitive capacity of a learner (de Jong, 2010; Rogers, 2010; van Merrienboer & Sweller, 2010). These elements - extraneous load, intrinsic load, and germane load have been previously defined in this dissertation, but are reiterated in *Table 1* below (Mayer, 2014a).

Table 2 Elements of Cognitive Load (Derived by Mayer, 2014)

Type	Definition	Cause
Extraneous	Cognitive processing that does not serve the instructional goal	Poor Instructional Design
Intrinsic	Cognitive processing for building a mental representation of the material as presented.	Complexity of material
Germane	Cognitive processing aimed at making sense of the presented material.	Learner's motivation to exert effort to learn

It should be stated that the primary focus of many research studies has been extraneous load as this is the aspect of cognitive load that is most influenced by the design and delivery of learning resources (DeLeeuw & Mayer, 2008b; Kester, Lehnen, Van Gerven, & Kirschner, 2006; Mayer, 2010a; Paas, van Gerven, & Wouters, 2007; Renkl, Hilbert, & Schworm, 2009; Schnotz & Kurschner, 2007; van Merrienboer & Sluijsmans, 2009; van Merrienboer & Sweller, 2010; Zumbach & Mohraz, 2008). Further, the examination of extraneous load was the impetus for CLT when Sweller (1988b) explored the challenges of problem-solving in mathematics education. Literature outlining the importance of each aspect of cognitive load as it pertains to learning is presented below.

2.4 Extraneous Load

Extraneous load is most aptly defined as cognitive processing that does not contribute to learning (Mayer & Moreno, 2010a). Leppink, Paas, van Gog, van der Vleuten, and van Merriënboer (2014) suggested extraneous load, 'arises from suboptimal instructional methods that require the learner to engage in cognitive processes that do not contribute directly to the construction of cognitive schemata (e.g., having to mentally integrate spatially or temporally separated but mutually referring information sources) and are as such unnecessary and extraneous to the learning goals' (p. 32). Paas, Renkl, and Sweller (2004) earlier outlined lined the benefits of schemata construction. Schemas are organizational units, which permit multiple elements of information to be treated as a single element according to the manner in which it will be used. Paas et al. (2004) suggests, "Knowledge organized in schemas allows learners to categorize multiple interacting elements of information as a single element, thus reducing the burden on working memory. After extensive practice schemas can become automated, thereby allowing learners to further bypass working memory capacity limitations. From an instructional design perspective, it follows that designs should encourage both the construction and automation of schemas" (p. 2).

Other aspects of extraneous load that have an impact on learning come from designs of materials that split the attention of the user between two or more relevant pieces of information. This phenomenon has been called the *split-attention affect*. Roodenrys, Agostinho, Roodenrys, and Chandler (2012) demonstrated the impact of split-attention on learning. In their experiment, Roodenrys et. al. (2012) used three experimental conditions. The first condition was called the conventional split attention group where a diagram and explanatory text were separated from one another forcing the learner to hold information in working memory to make integration more challenging. The second experimental group was presented with the same information in an integrated fashion, such that the explanatory text and accompanying diagram were presented as one resource. Finally, the third experimental group was taught how to manage the separation of information using guidance principles. The results of the performance measures suggest that experimental group 1 performed least effectively on recall of information. It was also determined that the greatest impact on learning was based on the instructor controlled design of materials. This was demonstrated by the performance results of the group where the instructor integrated the materials for the learner. These findings support previous research results investigating the impact of split attention (Dutke & Rinck, 2006; Mayer, 2010a). The proximity of information in time (*temporal contiguity*) and space (*spatial contiguity*) have been critical areas of CLT research (Mayer & Moreno, 2010a; Mayer & Moreno, 2003; Moreno & Park, 2010), and as stated above, have had impacts on learner performance.

When materials are presented with additional information that counters the intended message, learning will be negatively impacted. This principle is called the *coherence principle* and it occurs when extraneous additional information is added to primary learning materials. Mayer and Moreno (2010a) highlighted this principle by describing an educational situation where explanatory information of a process is presented as an animation along with narration describing the same process, but not necessarily the accompanying narration of the animation. This impact was initially highlighted in test results presented by Moreno and Mayer (2000). In this study, it was shown that the addition of superfluous sounds impacted the learner's ability to retain and recall information. Moreno and Mayer (2000) concluded that their results were consistent with the idea that auditory adjuncts can overload the learner's auditory working memory, as predicted by the cognitive theory of multimedia learning.

A similar effect to that described above can be found in the use of additional images within learning materials. Sanchez and Wiley (2006) found that although illustrated text can enhance comprehension, illustrations can also sometimes lead to poor learning outcomes when they are not relevant to understanding the text. This phenomenon is known as the *seductive details effect*. While the mechanism of the seductive details effect is not fully understood, Sanchez and Wiley (2006) suggested that it is likely the result of distraction, disruption or diversion. In light of the previously mentioned split attention principle, it is plausible that the addition of irrelevant information could serve as a distraction for learning.

The final principle that will highlight the impact of extraneous load on learning is termed the *dual channel principle*. This is the assumption that proposes that learners have separate channels for processing verbal and pictorial material. This notion is derived from the work of Paivio (1986). The dual channel principle proposes that information should be presented to two channels at once such that information should not overload one channel. However, careful consideration must be given to what is presented in both channels simultaneously as redundant information in both the auditory and visual channels have been shown to be detrimental for learning (Craig, Gholson, & Driscoll, 2002; Mayer & Chandler, 2001; Moreno & Mayer, 2002; Muldner, Lam, & Chi, 2014). This phenomenon has been called the *redundancy principle* (Brunye, Taylor, & Rapp, 2008; Hoffler & Leutner, 2007; van Merrienboer & Sweller, 2010). To mitigate the impact of redundancy, Mousavi et al. (1995) suggested that corresponding text should be removed from a narrated presentation of the same material.

2.5 Intrinsic Load

Intrinsic load is that portion of cognitive processing dedicated to the resolution of information that is being presented (Schnotz & Kurschner, 2007; Sweller & Chandler, 1994; van Merrienboer & Sweller, 2005, 2010). This processing can be described as the load imposed by the inherent level of difficulty of the material to be learned (Mayer, 2010a). Mayer and Moreno (2010a) suggested that heavy intrinsic load occurs when the essential material is complex, face paced, or unfamiliar to the learner.

In light of the description provided above, pacing is one critical aspect of information delivery that would have an impact on learning (Schnotz, Bockheler, Grzondziel, Gartner, & Wachter, 1998). As one would anticipate, materials that are presented too fast for a learner to process would have a negative impact on learning. However, the impact of pacing is not strictly on increased speed of presentation. Schnotz and Rasch (2005) demonstrated that information that was presented too slowly to learners also had a negative impact on learning. Increased intrinsic load caused by issues related to pacing are often mitigated by the inclusion of user controls for learning resources (Le Bohec & Jamet, 2005; Mayer & Moreno, 2002).

The addition of user controls emphasizes the next principle often used to mitigate the impact of heavy intrinsic load. That is the *segmenting principle*. The segmenting principle is often incorrectly referred to as 'chunking'. Chunking more accurately describes the grouping of information into schema that is done automatically within the learner, rather than intentional grouping of information done through a design process (van Merrienboer & Sweller, 2010). The segmenting principle proposes that information should be organized into smaller, more manageable units of information. Several experiments (Mayer, 2014b; Mayer, Dow, & Mayer, 2003) have shown that learners presented with continuous information without breaks or the ability to regulate the pace of instruction are outperformed on retention tasks and transfer tasks, compared to learners who had materials segmented with the addition of controls to manage the pace of instruction. Moreno (2007) more recently confirmed the above results, demonstrating that college students were better to transfer a set of teaching principles to novel scenarios when they were taught with segmented videos, compared to learners who were taught using non-segmented videos of exemplar standards with identical content.

The segmenting principle is assumed to work by reducing the strain on working memory that can occur with continuous presentation of information. Through segmentation, the working memory capacity of the learner is not overloaded and information is able to transfer into long-term memory unimpeded (Mayer & Moreno, 2010a). In this regard, segmenting acts as a buffering system that enables the learner to regulate the flow of information for meaningful storage.

The final aspect of intrinsic load that is difficult to overcome is related to unfamiliar knowledge. This seems like a paradox since all new information will be relatively unfamiliar to the learner. However, preparing the learner for newly presented information will increase the proficiency of learning (Mayer, 2010a; Mayer & Moreno, 2010a; Mayer, 2014a; Mayer, 2014b; Reed, 2006; van Merrienboer & Sweller, 2010). Mayer, Mathias, and Wetzell (2002) demonstrated that presenting learners with definitions of key components before concepts were presented helped on transfer and retention of learning. In their experiment, Mayer et al. (2002) allowed learners to explore an illustration of a car's breaking system that provided descriptions of the elements. When this pre-training had been completed a narrated animation was presented to the learners. Those who received the pretraining opportunity outperformed those learners who were only given the narrated animation on transfer and retention tasks. Mayer and Moreno (2010a) suggested that pretraining is effective when names, locations and behaviours of key components are presented before the concept is presented to the learner.

2.6 Germane Load

Germane load is the final element of CLT and is the most challenging aspect to influence through instructional interventions or strategies. This is the portion of learning that requires the learner to interpret information in a meaningful way so that it can be organized and stored into long-term memory (Paas & van Gog, 2006; Schnotz & Kurschner, 2007; Van Merrienboer, Kester, & Paas, 2006; van Merrienboer & Sweller, 2010). It is the portion of our total cognitive capacity that we try to increase since its purpose is the organization and storage of meaningful information into long-term memory.

In spite of the assumption that generative or germane processing occurs solely within the learner, Moreno and Mayer (2010) have suggested strategies for increasing germane processing, which is the intent of learning. Many of these strategies are predicated on appealing to motivational factors of the learner (Mayer, 2014a). Moreno and Mayer (2010) suggested that using multimedia tools would increase learner motivation by appealing to various sensory modalities simultaneously. Moreno and Valdez (2005) demonstrated that learners who were presented with images and text outperformed learners who were only presented text for the purposes of learning scientific concepts. Similar findings have been found in more recent studies using more complex multimedia resources like animations and videos (Moreno & Ortegano-Layne, 2008).

Moreno and Mayer (2010) suggested that the *multimedia principle* is effective for motivation because it aids in off-loading information to two separate channels (i.e. dual channel assumption (Paivio, 1986)). Further, 'applying the multimedia principle is especially important for fostering learning when learners have little or no prior knowledge in a domain (i.e. novice learners)' (Moreno & Mayer, 2010 p. 157). This same concept was believed to help learners of different abilities, such as spatial ability. Mayer and Sims (1994) suggest that students with high spatial ability benefit more significantly from simultaneous presentation of animations and narration than their lower spatial ability counterparts. Mayer and Sims (1994) proposed that this was due to lower spatial ability learners requiring additional guidance and cues to process dynamic information. This will be explored further within this dissertation as this relates to the primary focus of the present research.

Part of motivating students depends on the utility of the information that is being learned. From this perspective the *personalization principle* has been suggested as a way to motivate students to learn (Moreno & Mayer, 2010). The personalization principle is predicated on self-referential effects found in experimental psychology (Symons & Johnson, 1997). The self-referential effect is the notion that personalization promotes more active processing, and hence more meaningful processing of new information if the learner can relate the material to their personal experiences or circumstances. In this regard, the learner is thought to be more intimately involved in the learning process compared to being a passive observer (Moreno & Mayer, 2010).

2.7 Summary of the Cognitive Load Effects on Learning

The foregoing section outlined the three aspects of CLT. Within the discussion on each section research literature supporting these aspects was presented. Some of the suggestions seem obvious based on our own experiences as learners, for example, pacing as a means to ensure the learner can effectively process information. This same premise can also have negative impacts on learning if certain thresholds are not met. That is, if pacing is too slow, it can have the same effect on learning outcomes as pacing that is too quick for meaningful processing. These sections were intended to highlight the principles of CLT that both positively and negatively impact learning. The next section will explore how cognitive load has been measured in the research literature.

2.8 Measures of Cognitive Load

Measuring cognitive load has been a popular research topic within the academic literature over the past two decades (Antonenko, van Gog, & Paas, 2014; Brünken et al., 2003; Paas et al., 2003). The classification for measuring cognitive load was aptly broken into categories based on objectivity and causal relationship earlier by Brünken et al. (2003). *Table 3* below highlights the relationship between these categories.

Table 3 Categories of Measurement for Cognitive Load – Derived from (Brunken, Plass, & Leutner, 2003)

	Causal Relationship	
Objectivity	Indirect	Direct
Subjective	Self-reported invested mental effort (Kühl et al., 2011b)	Self-reported stress level (Borg, Bratfisch, & Dorni'c, 1971)
Objective	Physiological & Behavioural measures (Van Gerven, Paas, Van Merrienboer, & Schmidt, 2004): - Galvanic skin response - Heart rate - Blood pressure - pupil dilation Learning outcome measures	Brain activity measures (Antonenko et al., 2014; Stroobant & Vingerhoets, 2000): - Functional Magnetic Resonance Imaging (fMRI) - Electroenchephalogram (EEG) - Transcranial Doppler Ultrasonography Dual-task performance

Table 3 highlights the wide and ranging methods used to explore the notion of cognitive load. In spite of the greater number of objective methods and measures for measuring cognitive load, most research uses subjective methods for evaluating cognitive load (Leppink et al., 2014). Subjective measures of cognitive load have shown to be correlated with performance or learning outcomes. Kühl et al. (2011) found that there was a uniform negative correlation between

perceived level of difficulty (i.e. task complexity) and learning outcomes on the various learning tasks participants completed (verbal factual knowledge: $r = -.29, p < .05$; pictorial recall: $r = -.47, p < .01$; transfer tasks: $r = -.52, p < .01$). This shows that individuals who rated learning tasks as more difficult also did not perform well on these tasks. However, when participants used subjective measures of mental effort no significant relationship was found with performance (pictorial recall ($r = .15, p = .20$), transfer ($r = - .04, p = .73$) or verbal factual knowledge ($r = .20, p = .10$). Inconsistencies like the above results have lead to subjective scales being criticized and more efforts being placed on objective measures of cognitive load. Further, as Brünken et al. (2003) suggested, the relationship between perceived mental effort and cognitive load is not clearly defined. It would seem intuitive that effort is an analogous term for load, given how cognitive load and processing are defined within the academic literature. However, the term processing does imply a level of required effort regardless of the load imposed on the learner.

Advances in neuroimaging have sparked a renewed interest in using these tools to explore educational problems, like cognitive load (Whelan, 2007). As Antonenko et al. (2014) stated: 'Neuroimaging has enabled scientists to open "the black box" of neural activity that underlies learning. It seems timely, therefore, to consider how educational researchers may employ the increased understanding of brain function to explore educational questions' (p.51). Brünken, Seufert, and Paas (2010) discuss objective measures of cognitive load such as physiological variables, and stated that the benefits of techniques like imaging and eye-tracking enabled continuous observations of cognitive effort. Conversely, cognitive effort or load is not typically experienced throughout the duration of a learning task. Therefore, subjective measures are relying on the individual to make a general observation or 'average' their perceived mental effort. For this reason, it might be appropriate to consider a combination of both objective and subjective measures of cognitive load.

2.9 Importance for the Present Study

The previous section highlighted the methods typically employed for measuring cognitive load. As was stated, subjective measures are the most widely used in studying cognitive load. However, subjective scales are inconsistent and rely on the participant to make generalizations about their perceived level of effort or the perceived level of difficulty using various learning materials. The benefits of subjective measures are the ease of use and the relatively innocuous manner in which they impact the natural learning environment.

Conversely, greater emphasis on neuroimaging and neuroscientific methods have been presented in recent research (Antonenko et al., 2014). These methods seek to directly measure changes in physiological responses during the course of a learning task. While these measures provide a continuous glance at the individual's responses during a learning task, the instruments and methodologies are not subtle due to their interference with the natural learning environment. That is, most participants do not learn within a functional magnetic resonance imaging magnet, or with eye-tracking devices attached to their body.

The benefits of both subjective and objective methods can be realized within a study of cognitive load if both subjective and objective methods were simultaneously employed. The present investigation proposes that these benefits can be realized, and the disadvantages can be mitigated or counterbalanced. Few prior studies have attempted to utilize neuroscientific instruments coupled with psychological metrics like subjective scales to resolve or explore educational problems such as has been described thus far. The next section of this literature review will examine the different types of images that are used in educational materials. This discussion will further define the research problem and questions of the present investigation.

2.10 Images

Everyone has likely heard the idiom, ‘a picture is worth a thousand words’. In the same vein, another idiom comes to mind. That is, ‘less is more’. In the context of the present discussion, if pictures are worth a thousand words, and less is more, than what is being imposed on learners when we use static or dynamic images for learning? This debate has surfaced in the academic literature over the last two decades as technological advances for education have enabled instructors to incorporate more advanced images into their learning materials (Hegarty & Waller, 2004; Khalil, Paas, Johnson, & Payer, 2005a; Lowe, 2000, 2004). This discussion will examine the research literature related to the use of static and dynamic images for learning.

2.11 Static and Dynamic Images for Learning

The descriptions of static and dynamic images were previously presented within this dissertation. The primary difference between image types is the change of perspective or content in time and space (Hoffler & Leutner, 2007). Static images are relatively easy to describe as this term implies a graphical depiction or illustration of information in the form of a diagram or a photograph. In contrast, dynamic images could include videos, animations, interactive animations, or virtual reality models or scenes (Hegarty & Waller, 2004; Hoffler & Leutner, 2007; Mayer, Hegarty, Mayer, & Campbell, 2005; Tversky, Morrison, & Betrancourt, 2002).

Static images have been suggested to be beneficial for learning because they do not overload or impose heavy cognitive demands on the learner (Mayer et al., 2005). Specifically Mayer et al. (2005) suggested that static images are preferential for learning because, static illustrations with accompanying printed text reduce extraneous processing and promote germane processing, compared with narrated animations. These findings can be scrutinized based on the following assumption. That is, there is likely more influence contributed by the text or narration than the image alone. In the study by Mayer et al. (2005), images were not examined in isolation of additional supporting information. The effects observed could likely be the result of pacing (Hoffler & Leutner, 2007; Stiller, Freitag, Zinnbauer, & Freitag, 2009), where static images offer inherent benefits compared to dynamic images without user controls.

The appeal of dynamic visualizations for learning has been supported by several studies within the academic literature (Ainsworth & VanLabeke, 2004; Arguel & Jamet, 2009; Ayres & Paas, 2007; Bodemer, Ploetzner, Bruchmuller, & Hacker, 2005; Boucheix & Schneider, 2009; Chandler, 2009; Cook, 2006; Hoffler & Leutner, 2007). The benefits of dynamic visualizations are related to the ability to convey complex relationships in time and space (Garg, 1998; Garg et al., 1999a), as well as illustrate the sequence of stages in a process or concept (Hoffler & Leutner, 2007). Many of the studies examining the uses of dynamic visualizations have conveyed a specific type of information to the learner, specifically processes (Mayer et al., 2005), or concepts that are better suited for an animated model.

In spite of these proposed benefits and findings, there has been no consensus on which image type is best for supporting learning. There are likely several reasons for this. First, the subject matter used for each of these studies has typically been a concept or process that is intended to demonstrate changes over time. For example, how lightening is produced, or how the brake system of a car works (Mayer et al., 2005). Second, most of the studies comparing image types do so with the inclusion of other factors (i.e. narration and/or text) that influence learning (Paas et al., 2007; Park, Lee, & Kim, 2009; Rasch & Schnotz, 2009; Ruiz, Cook, & Levinson, 2009). Thus far, the best predictor for determining the efficacy of image type is related to the ability of the user, and not the characteristics of the image (Nguyen et al., 2012). That is, the spatial ability of the learner may be the best method for determining the effectiveness of incorporating a static or dynamic image into learning materials (Meijer & van den Broek, 2010; Nguyen, 2012; Nguyen et al., 2012).

The next section of this literature review will explore the relationship between cognition and cerebral blood velocity. The intention is to emphasize the relationship between the demand for blood in the brain and cognitive processing. As discussed above, cognitive demands imposed by image type may have an impact on learning. By exploring the relationship between these demands and the changes in blood velocity it is assumed that a new, less invasive method of directly measuring cognitive load can be accomplished.

2.12 Cerebral Blood Velocity and Cognition

The origins of investigating the relationship between blood flow and cognition can be traced to 1881, when the Italian physiologist Angelo Mosso recorded the pulsation of the human cortex in patients with skull defects following neurosurgical procedures (Raichle, 2001b). Mosso demonstrated that these pulsations increased regionally during mental activity (Raichle, 2001b). A few short years later, Roy and Sherrington (1890) demonstrated that the brain ‘expands’ in response to stimulation. This expansion was due to an influx of blood as a result of the stimulation.

More direct investigations examining the relationship between cognitive processing and cerebral blood flow occurred in 1928 when a surgical resident of Harvey Cushing explored the relationship between visual processing and blood flow to the occipital cortex (Raichle, 2001b; Stroobant & Vingerhoets, 2000). John Fulton (1928) studied a patient who had undergone the removal of an arteriovenous malformation of the occipital cortex. The malformation caused a bruit (i.e. sound or murmur) to occur in the patient. Removal of the malformation did not cure this patient of the bruit. Thus, Fulton was able to observe that the blood flow to the region was responsible for the bruit. When the patient engaged in different visual activities the intensity of the bruit changed. Blinking caused a mild increase in the bruit, while reading caused a striking increase in the bruit. Fulton concluded that the rate of flow of blood through the brain increases as a result of sustained mental effort (Fulton, 1928).

These above examples report the outcomes of observations made during purely opportunistic periods. In both cases the observations relied on access to an open skull and exposure to a brain. Fortunately, measuring changes in blood flow velocity can now be achieved with noninvasive techniques. Aaslid et al. (1982) described one such technique that relies on Doppler ultrasonography. This method will be discussed in further detail below.

Fox and Raichle (1986) demonstrated that in normal, awake adults, stimulation of the visual or somatosensory cortex resulted in dramatic increases in regional blood flow velocity. These increases in blood flow correlated with glucose utilization. The level of glucose utilization was in excess of the change in oxygen consumption suggesting that neuronal activity can be supplied by glycolysis alone (Raichle, 2001b). Raichle (2001) suggested that increases in neuronal activity in the cerebral cortex are associated with increased oxidative metabolism of glucose. However, he also cautioned that blood flow increases are not solely a result of neuronal metabolism. Other cells, such as astrocytes, also undergo oxidative metabolism and contribute to oxygen demand in the brain (Magistretti, Sorg, Yu, Martin, & Pellerin, 1993). Regardless, the increase in oxygen demand is still the result of stimulation of the cortex since support cell metabolism and neuron metabolism is assumed to be coupled and occurring at the same time (Magistretti et al., 1993; Raichle, 2001b).

The historical evidence and recent research presented above highlight the relationship between cognitive processing and increased demands for blood in the brain. As Duschek, et. al (2008) stated, 'cognitively induced changes in cerebral perfusion result from the tight coupling between neural activity and brain metabolism' (p. 81). In spite of this assertion there are some potential areas of caution when relying on blood flow velocity as a measure for cognitive processing.

Using blood flow velocity as a measure of cognitive effort has been challenging for several reasons. First, the level of blood velocity in the brain increases in response to any cognitive activity, even activity that is inhibitory, since this process requires energy derived from cellular metabolism as well (Raichle, 2001b). Therefore, determining the difference between mental effort and no effort must be accomplished through careful planning and design of experiments measuring cognitive processing. Also, blood flow velocity is slow to respond to metabolic demands as a result of cognitive processing. The delay or lag in response is due to the fact that oxygen reserves are available throughout the brain and these are depleted before velocity to these regions increases. A consequence of this is that velocity elevation continues for some time after cognitive processing has subsided or diminished (Raichle, 2001b). These issues have been resolved with careful planning and design of experimental conditions.

2.13 Transcranial Doppler Ultrasonography and Cognition

Transcranial Doppler (TCD) ultrasonography has been used in several research studies as a method to measure changes in cognitive processing (Aaslid et al., 1982; Bakker et al., 2014; Deppe, Knecht, Lohmann, & Ringelstein, 2004; Duschek & Schandry, 2003; Hartje et al., 1994; Kelley et al., 1992; Stroobant & Vingerhoets, 2000). TCD relies on the physical basis of the '*Doppler effect'*. Doppler sonography is a frequency shift that results from relative movement between a source (e.g. erythrocytes in an artery), and the receiver. The shift in frequency that occurs when ultrasound signals are reflected by erythrocytes in the blood stream of a vessel is used to determine the velocity of blood flow. The size of the frequency shift is directly proportional to the velocity of the blood stream (Duschek & Schandry, 2003).

Measuring mere cerebral blood flow (CBF) in the brain will not tell us much about the changing demands for oxygen as a result of cognitive processing (Slutsky et al., 2010). Further, accurate measures of CBF are subject to changes in dilation of arteries and other physiological conditions like the concentration of CO_2 in blood (Dirngal, Edvinsson, & Villringer, 2002; Duschek, Werner, Kapan, & Reyes del Paso, 2008). Duscheck et al. (2008) commented on using arterial velocities rather than CBF and stated:

> Unlike the diameters of the small vessels, those of the basal cerebral arteries, which are insonated by transcranial Doppler sonography, remain virtually unchanged under varying conditions of stimulation. Therefore, blood flow changes in these arteries do no result from their own vasomotor activity, but reflect changing metabolic rates in their perfusion territories (p. 81)

Therefore, TCD studies examining the relationship between brain activity and cognitive processing usually describe blood flow velocity (BFV) data rather than absolute values of CBF (Deppe et al., 2004; Goldberg et al., 1998; Slutsky et al., 2010).

Kelley et al. (1992) were among the first to explore the uses of TCD as a means to measure circulatory changes in the cerebral arteries during cognitive activity. In their study, Kelley et al. (1992) demonstrated that TCD could be used to measure generalized increases of blood flow velocity above baseline measurements during a cognitive activity (e.g. video game play). These results suggested that this non-invasive technique has the potential to correlate selective cerebral artery flow dynamics with cognitive activity.

Several years ago, Stroobant and Vingerhoets (2000) complete a systematic review of the literature related to the use of TCD as a means to measure cognitive processing. They concluded that TCD provided the affordance of being able to measure moment-to-moment changes in blood flow velocity during cognitive tasks. Their review provided further evidence to support the appropriate location to measure cognitive processing of visual information. *Table 4* below outlines studies where velocity of the right Middle Cerebral Artery (MCA) using TCD has been employed as a method for measuring changes in cognitive processing during learning tasks.

Table 4. Evidence to Support the Right MCA as the localization of visual processing

Author	N	Stimuli	Result
Harders et al. (1989)	24	Illumination of visual field, looking at images for discrimination (comparison task)	R > L signal
Kelley et al. (1992)	21	Computer video game – visual	R > L signal
Harders et al. (1989)	70	Spatial imagination	R > L signal
Rihs et al. (1995)	14	Visual – Looking at faces and patterns	R > L signal
Bulla-Hellwig et al. (1996)	28	Visuospatial tasks	R > L signal
Cupini et al. (1996)	22	Visuospatial working memory	R > L signal
Vingerhoets and Stroobant (1999)	90	- Visuospatial design comparison - Mental rotation of figures	R > L signal

Note: These studies were primarily interested in determining which hemisphere was responsible for specific cognitive functions. The Results indicate the right hemisphere had an increase in CBV, as indicated be the directionality of comparison (i.e. R > L). Meaning the right hemisphere was more active.

The use of TCD as a method to measure neurophysiological responses to learning tasks has various benefits over newer more sophisticated neuroimaging methodologies. It should be noted that fewer studies in recent years have employed TCD to measure cognitive processing from a learning perspective, due to the advances in neuroimaging. In spite of this trend, TCD does continue to offer several advantages over newer neuroimaging technologies. These comparisons will be made in the following section of this literature review.

2.14 Comparison of Transcranial Doppler Ultrasonography and Neuroimaging

The development of functional Magnetic Resonance Imaging (fMRI) in the early 1990's created a great amount of enthusiasm in cognitive neuroscience (McRobbie, Moore, Graves, & Prince, 2010). The basic premise of functional magnetic resonance imaging is that active areas of the brain (e.g., during learning) will consume more oxygen. Oxygen consumption by neurons leave a trace that can be detected by pulses rebounding in powerful magnetic fields generated by an MRI scanner. Volumetric images of the magnetic fields are then compiled from 'blood oxygenation level dependent' (BOLD) signals. These signals can be mapped to display the neural correlates of cognitive tasks. That is, the signals are used to produce a map that highlights relative changes in oxygen consumption within the brain during 'activity' or cognitive processing (Kolb & Whishaw, 1996; McRobbie et al., 2010).

The first study to make the connection between CLT and the potential for fMRI to measure the attributes of cognitive load was presented by Whelan (2007). Using an analogous phrase to that of Bruer (1997), Whelan's (2007) postulate that cognitive load aspects could be localized within the brain using fMRI is a 'leap too far'. Table 5 below highlights the connection between cognitive load elements and research findings using fMRI methodology.

Table 5 Summary of fMRI results indicating CLT aspects – Derived from (Whelan, 2007)

Load	Modality	Task	Active Regions	References	Conclusions
Intrinsic	Verbal (Audio)	Verbal reasoning – Syllogisms	- Operculum and triangularis in the inferior frontal lobe - Dorsolateral prefrontal cortex (DLPFC)	(Newman, Just, & Carpenter, 2002)	The right DLPFC serves as a control mechanism to reduce interference of competing information sources.
	Visual	Stroop Test (e.g. split attention task)	- Right DLPFC	(Banich et al., 2000)	

Load	Modality	Task	Active Regions	References	Conclusions
Extraneous	Audio & Visual	Sentence comprehension (read and listen)	- DLPFC - Left inferior frontal gyrus - Broca's and Wernicke's areas	(Michael, Keller, Carpenter, & Just, 2001)	DLPFC is again active and is assumed to be responsible for modulating attention across sensory modalities
	Audio & Visual	Multitask – Sentence comprehension and mental rotations	- Temporal and parietal regions, prefrontal cortex	(Just et al., 2001)	
Germane	Audio & Visual	-Incentivized games to examine motivation. - Decision-making tasks to determine risk/reward	Thalamic, striatal, and orbitofrontal brain regions, the medial hypothalamic/preoptic area, the midbrain/pons, the midline and intralaminar thalamic nuclei, and the medial prefrontal and anterior cingulate areas	(Ernst et al., 2004; Kirsch et al., 2003; Sewards & Sewards, 2003)	Germane processing is widely interspersed throughout the brain and is difficult to localize.

Table 5 is used to highlight the attempts to make connections between the aspects of cognitive load and the use of fMRI. Functional neuroimaging has a seductive appeal for researchers because it provides a time and place for mental activity. However, this is somewhat misleading. First, fMRI works on the principle of relative activity. That is, the indicated areas (referred to as lit-up areas due to image brightness) on an fMRI scan are relatively 'more active' than other adjacent areas (Kolb & Whishaw, 1996; McRobbie et al., 2010; Raichle, 2001a). This misconception hides the truth that other areas are also active during cognitive processing, but not as active as the areas indicated by brightness intensity. Further, fMRI data has a high spatial fidelity, but a relatively low temporal fidelity (McRobbie et al., 2010), and it is not sensitive

enough to detect ‘real-time’ changes in cognitive process. Finally, the above research is very similar in approach and methodology. These findings are overlapping and should not be used as generalizations about the localization of cognitive load aspects within the brain. As stated previously, early research by Lashley (1950) and Hebb (1949) highlighted the notion that memories could not be localized, and memories are thought to be spread throughout the cortex. Likewise, loads imposed by different presentations of information or learning tasks are likely the result of activation in a number of different brain regions. Not all intrinsic or extraneous processing imposed on a learner can be assumed to be isolated to the DLPFC as the results above suggest. For these reasons, a more globalized approach to measuring cognitive processing is proposed for the present study. Transcranial Doppler ultrasonography provides the affordance of near ‘real-time’ observation of changes in the demand for blood resulting from cognitive processing (Kelley et al., 1992; McKiernan, Kaufman, Kucera-Thompson, & Binder, 2003; Stroobant & Vingerhoets, 2000).

To make the comparison between fMRI and TCD the following analogy to internet traffic is offered. If one wishes to monitor changes in internet traffic of an institution, the best method for measuring overall traffic would be to measure the average traffic flow at the main servers during different times to establish a baseline. Following an intervention or an event, traffic at the servers would be measured again as a means for comparison. Identifying the users of the internet does little in telling us how volume has changed. This is akin to the above situation where fMRI provides a geographical depiction of where activity is occurring, whereas TCD measures the changes over time in a generalized area.

2.15 Implications for Brain-Based Learning

The brain-based label has been applied to theories of development and learning, learning principles and instruction guides, training methods, and educational products (Sylvan & Christodoulou, 2010). Brain-based learning appears to be a paradoxical statement since all learning is essentially the result of activity within the brain. However, within education the phrase 'brain-based' refers to a sub-discipline that subscribes to the notion that neuroscience research findings can be directly applied to instructional practices to have specific or targeted effects on the learner (Zambo & Zambo, 2011). Misconceptions such as those highlighted above through the use of fMRI data contribute to fuelling the brain-based movement (Goswami, 2006). The appeal of being able to selectively target brain regions through instruction seems surreal and is further supported by generalized assumptions like those provided by Whelan (2007). However, the more realistic contention is that instructional interventions are not able to selectively isolate brain regions. Further, there is no evidence to support the idea that by isolating brain regions, learning will become more efficient (Dekker et al., 2012). For this reason, the present research seeks to provide answers to more general questions related to the relationships between perceived effort, physiological response and performance.

2.16 Summary

This literature review presented the different aspects of CLT and research to support these elements of how information is acquired and stored. Further discussions and literature was presented to illustrate the different ways that cognitive load has been measured. The trends in cognitive load measurement have shifted from the primary use of subjective rating scales to more objective measures using physiological variables. It is apparent to many who actively review the

CLT literature that the jumps and leaps of measurement methodologies have been greatly influenced by neuroimaging (Antonenko et al., 2014; Whelan, 2007). However, as discussed these leaps may be misleading and not providing answers to fundamental questions related to the nature of cognitive load and the effect on learning.

2.17 Restatement of Hypotheses

Based on the research literature presented in the foregoing, the research hypotheses for the present investigation will be restated to place them in the proper context with more supporting evidence. It is anticipated that evidence presented here will demonstrate:

i. Learners with higher spatial ability will show a decrease or reduction in mean cerebral blood velocity in the right middle cerebral artery compared to their low spatial ability counterparts during learning tasks using static and dynamic images.

ii. Mental effort, as perceived by the research participant, will be positively correlated with a mean percent increase in cerebral blood velocity.

iii. Performance on learning tasks will be better in situations where the learner was presented with a more complex image during the information acquisition phase. The increased fidelity of images (e.g. depth cues) will have a positive effect on retention of information, and hence learning and performance.

Chapter Three: **METHODOLOGY**

3.1 Introduction

The present study examines the physiological responses of the brain during learning with different types of images and the relationship to performance and perceived mental effort. The methods used for the present study rely on changes in mean cerebral blood velocity (CBV) of the right middle cerebral artery (MCA), which has been demonstrated to be responsible for supplying blood to a generalized region of the brain where visual information is processed for visual perception (Deppe et al., 2004; Duschek & Schandry, 2003; Kelley et al., 1992; Mergeche, Bruce, Sander-Connolly, & Heyer, 2014; Schmidt et al., 1999; Stroobant & Vingerhoets, 2000). To ensure that the observed changes in CBV are the result of cognitive processing rather than resulting from external factors like stress or variations in breathing, end-tidal CO_2 data were also collected to monitor variability, as has been done in previous transcranial Doppler research (Deppe et al., 2004; Kelley et al., 1992; Stroobant & Vingerhoets, 2000). In contrast to prior research, the present study also examined the relationship between performance, spatial ability and perceived mental effort. Analysis of the relationship between these variables will highlight difference in the physiological response based on spatial ability, presentation modality and learner performance. The goal is to determine the impact digital media has on learning in individuals with different spatial abilities, providing physiological evidence for cognitive load.

3.2 Overview

The previous two chapters provided a historical overview and context for the present study. The findings from early physiologists like Mosso (1881), and Roy and Sherrington (1890) (Davis, 2004; Raichle, 2001a) were presented as evidence of localized changes in blood velocity in the brain resulting from cognitive processing. Further, an overview of CLT was presented as it serves as the theoretical focus for the present study. During the discussion on CLT a review of the prior methodology used to measure cognitive load was presented. This chapter will serve as a synthesis of all of these ideas to outline how indices of cognitive load were measured in the present study, and how these methods could be used in future cognitive load research.

The overarching purpose of the present study is to examine the relationship between physiological changes in the brain and performance on learning tasks using static and dynamic digital media. Further, the present study juxtaposes physiological changes and methodologies with those that are typically used in cognitive load research, specifically subjective rating scales of perceived mental effort (Paas et al., 2003). The goal is to determine the extent of the relationship between cognitive processing, performance and perceived effort. Cognitive Load Theory (CLT) is a theoretical construct based on assumptions about the behaviour of the brain and underlying cognitive architectures. The methods presented within this research provide a direct approach to measure brain activity as it pertains to these assumptions. As with prior research (Nguyen, 2012; Nguyen et al., 2012), the present study assumes that there is a relationship between spatial ability and the level of performance in learning tasks. However, it has not been determined in the literature how this relationship is manifested in a physiological context.

3.3 Research Sample

The demographic data for the present study is outlined in *Table 6* below.

Table 6. Research Sample Demographic Summary

		Spatial Ability		Age		Highest Education Level		
Sex	N	Low	High	Low	High	Pre-Undergrad	Undergrad	Graduate
Female	10	8	2	18	39	2	3	5
Male	19	6	13	18	51	1	8	10

Note: Education level refers to level achieved or currently enrolled.

Participants were invited to volunteer for participation in their courses by the investigator. The protocol for recruitment met the Ethical Review Board standards at both the degree granting institution and the host institution where the research was conducted. This protocol required a letter of consent and a letter of information that explicitly outlined the intent and purpose of the study, as well as the time commitment required for the study. No compensation was given to the participants for their participation.

There were only two exclusionary criteria for participation in the study. The first exclusionary criterion is related to handedness of the participants. All participants in the study had to be right-hand dominant (Oldfield, 1971). The lateral organization of brain function is much more predictable in right-hand dominant individuals than their left-hand dominant counterparts (Kelley et al., 1992; Oldfield, 1971). For this reason, at the onset of the study participants were asked to identify their dominant hand. Left-hand dominant individuals were excluded from full participation in the study. Their data was discarded and not included for analysis purposes. Their participation and data was removed following the administration of the Mental Rotations Test. To ensure that all individuals were right-hand dominant, the Edinburgh Inventory for handedness was administered (Kelley et al., 1992; Oldfield, 1971).

The second exclusionary criterion was colour blindness. The tests used in this study relied on the ability to identify the colour of various structures with slight discriminations in some cases. Therefore, each participant was required to recognize different colours. No official test was given to determine the extent of colour blindness. The investigator relied on the participants to identify if they were deficient in colour identification and discrimination. None of those who participated in this study self-identified as being colour blind.

Two participants met the criteria for the study and completed a majority of the testing. However, their data was subsequently removed when they experienced adverse effects due to the physiological instruments used in the study. One participant became nauseated as a result of the transcranial Doppler probe, and another participant approached syncope as a result of a prior medical condition. In both instances the testing was stopped immediately and the participants were asked to remain in the test area until their symptoms subsided.

3.4 Overview of Information Required

To provide evidence to address the study's research questions, several variables were measured and collected in the present study. This section will outline those variables, the rationale for collecting these data, and the process for obtaining these data.

The first variable that was collected upon the participant consenting to participate in the study was the spatial ability score. Spatial ability or the ability for an individual to mentally rotate objects was measured using the redrawn mental rotations test developed by Peters et al. (1995). This was a reiteration of the prior mental rotations task developed by Vandenberg and Kuse

(1978). The newer version by Peters et al. (1995) was designed to mitigate gender bias that often resulted in the administration of the Vandenberg and Kuse (1978) instrument. For the present study the results of the mental rotations task were used as a categorical variable. A median split in performance of all participants was used to classify individuals into a high spatial ability group (H) or a low spatial ability (L) group for comparison purposes. In an ideal scenario a tertiary split would be used to separate participants such that those that tended towards the median or overall mean would be excluded. This would create a greater disparity in spatial ability that would possibly exacerbate the differences in physiological responses between high and low spatial ability learners. As will be discussed, one of the limitations of the present study was a lack of disparity in spatial ability for the participants.

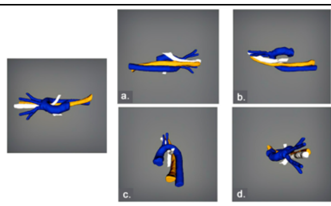
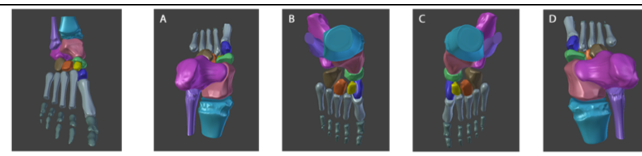
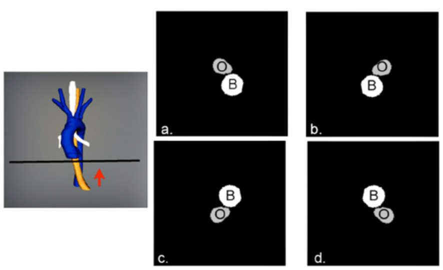
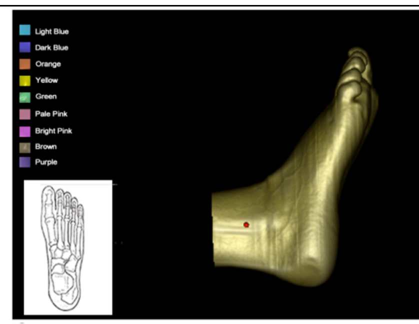
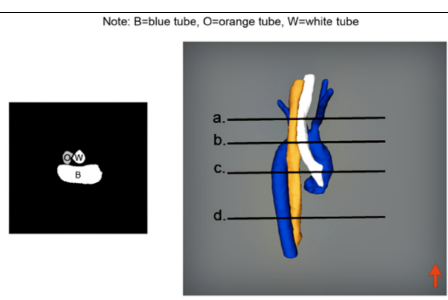
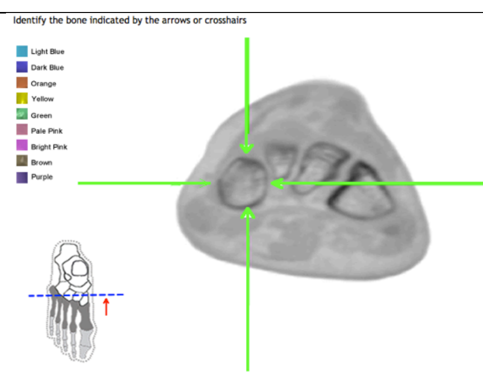
The second critical variable was test performance. Performance measures were based on the accuracy of responses to various question types. One of the tasks used was a previously validated instrument that measured the relationship between spatial ability and anatomical knowledge (Nguyen, 2012; Nguyen et al., 2012). *Table 7* below provides a matrix for the instruments used in the present study.

Table 7 Question Matrix for Testing

Image	Spatial Anatomy Test (SAT)			Human Ankle Test (HAT)		
Type	Rotations	Cross section	Planes 2	Rotations	Surface Identification	MRI Slice
Static	10	10	10	10	10	10
Dynamic	10	10	10	10	10	10

Each participant completed both a static and dynamic learning task and battery of tests. *Table 8* below provides an example of the types of questions asked in each of the tests for both the Spatial Anatomy Test (SAT), and the Human Ankle Test (HAT).

Table 8 SAT and HAT Question Examples

Spatial Anatomy Test (SAT)	Human Ankle Test (HAT)
1. Rotations Question Example	1. Rotations Question Example
	
2. Cross Section Question Example	2. Surface Identification Question Example
	
3. Planes 2 Question Example	3. MRI Slice Question Example
	

To randomize testing, the models (Tube or Ankle) and modalities (static or dynamic) were counterbalanced such that participants completed a dynamic task using the spatial anatomy tests and a static battery of tests using the ankle test, or vice versa. Each test consisted of 10 questions plus a subjective rating scale after every two questions to rate the level of mental effort expended on the previous question. This was a 9-point rating scale similar to that used in prior cognitive load research as a measure of perceived mental effort (Paas et al., 2003; Paas et al., 1994). The perceived mental effort was the third variable of interest for the present study.

The central variable for the present study was a correlate measure of cognitive processing as determined by changes in cerebral blood velocity (CBV) (cm/s) in the right Middle Cerebral Artery (MCA). To determine the extent of changes in CBV a baseline measure of mean CBV was taken for the various learning conditions; static and dynamic. To determine the affect of the learning or testing conditions a percent change from the baseline in each condition was calculated. Therefore, the changes within all participants were normalized and variations in sex, age, and physical condition were controlled.

Since variations in CBV can be influenced by a plethora of factors like blood pressure and respiration changes, these variables were also measured to ensure that the changes in CBV were the result of cognitive processing and not other factors like stress or test anxiety. End-tidal CO_2 values ($etCO_2$) measure the partial pressure of the carbon dioxide gas as a fraction (mmHg) of the last portions of air leaving the lungs, thus approximating circulating CO_2 in the blood. According to the metabolic theory, CO_2 formation increases during oxidative metabolism (respiration). Elevated levels carbon dioxide readily diffuse from the cells where it is produced to the smooth muscle of the blood vessels where it causes dilation. As a result, CO_2 plays a significant role in regulating cerebral blood flow and velocity (Klabunde, 2011) thus monitoring CO_2 output is critical in determining which variable; respiration or cognitive processing, is responsible for changes in CBV.

The final group of data is comprised of qualitative field notes or observations collected by the investigator, as well as follow-up comments provided by the participants in the study. This information will serve both as a means for comparison to the quantitative variables measured, as well as provide a richer picture of the results obtained. As Jaeger (1997) suggested, the strengths and weaknesses of qualitative and quantitative data collection methods compliment each other and the inadequacies of either method are mitigated by the other. For this reason, the field notes or observations will help to interpret underlying themes that may not be evident from quantitative measures alone.

3.5 Research Design

This research uses a mixed-methods explanatory design. This method consists of two distinct phases: quantitative data collection and analysis, followed by qualitative analysis (Ivankova, Creswell, & Stick, 2006). Creswell (2003) suggested that the researcher using this experimental approach should first collect and analyze the quantitative (numeric) data. The qualitative (text) data are collected simultaneously with quantitative data but analyzed second in the sequence to help explain, or elaborate on the quantitative data collected in the first phase. A schematic of this process is presented *Figure 6* below.

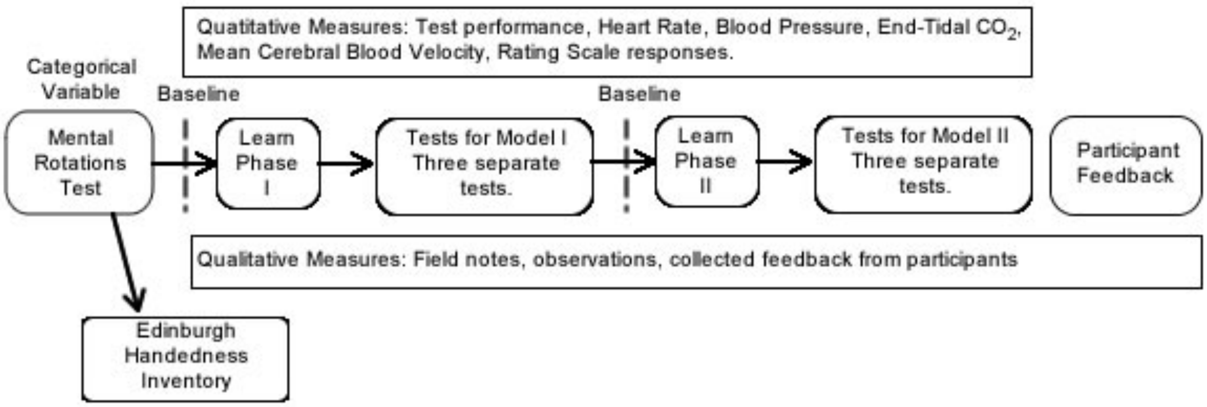


Figure 6. Mixed-Methods Sequential Explanatory Design for present study

The above figure is a graphical depiction of the research design for the present investigation. The figure highlights the sequence of test administration and learning phases, as well as the process of collecting both quantitative and qualitative data during participant testing sessions. That is, while the quantitative data was collected via various instruments, the researcher took field notes and made observations about the testing procedure of each participant.

The next section provides a detailed description of the data collection protocol that was used for the present study. This discussion is based on *Figure 6* above and will put the research design strategy in better context. Further, this will lead into the discussion about the type of data that was collected, and how it was analyzed or interpreted to answer the research questions presented within this dissertation.

3.6 Data Collection Protocol

As stated in the foregoing, spatial ability was the primary determinant of how effectively individuals can learn with complex images. For this reason, each participant completed a mental rotations task to determine their level of mental rotation proficiency (Peters et al., 1995). The results of this were not known until the completion of all tests.

Upon completion of the mental rotations task, participants were able to come to the laboratory where research was being conducted to complete the remaining learning tasks. Each session began with an introduction of the variables that were being collected, as well as the devices that would be used to collect this data. The recording devices that were used to collect the physiological data were attached to the participants and calibrated to establish standard measures.

Testing began with a randomized assignment for each model used for testing purposes; either static or dynamic, ankle or tube. In the end, each participant was tested with both the tube or ankle, but the order and sequence of modality (i.e. static or dynamic) was randomized. Based on the modality selected for the first test, a baseline measure of CBV was collected (See *Figure 7*). Upon completion of establishing a baseline, testing began with 3 sets of questions. Each set consisted of ten questions and five self-rating questions. Following the completion of the first phase, a short break was given to allow the participant to relax. Following this break, the alternative baseline values were determined and the final phase of testing resumed.

Upon completion of the testing, the researcher had an informal (i.e. unstructured interview) discussion with the participants about their experiences and their perception of the testing and their overall performance.

The next section discusses the variables collected for the present study along with a description of their significance and rationale for inclusion. A description of the data handling procedures and instruments used for collection and analysis purposes will follow.

3.7 Research Variables

The following section will describe the different types of variables that were collected for the present study. The methods of procurement and handling of these data are outlined.

3.7.1 Categorical Variables

Previous research has highlighted the relationship between spatial ability and effective use complex images for learning (Khalil, Paas, Johnson, & Payer, 2005c; Lowe, 2004; Mayer, 2014a; Meijer & van den Broek, 2010; Nguyen, 2012; Nguyen et al., 2012). The present study used scores derived from the mental rotations test by Peters et al. (1995) as a means to place participants into one of two categories, high spatial ability or low spatial ability. Classification on the participant was based on their relative standing amongst all other participants. The administration of this test was conducted using *Sakai CLE*, the Learning Management System (LMS) of the host University. This enabled the researcher to collect the responses for categorization purposes.

3.8 Physiological Variables

To establish a baseline for comparison of physiological changes during the different learning conditions, participants were asked to perform two baseline attention focus tests. The first test was intended to establish the resting physiological values during static learning. For this test, participants were asked to observe a static object with stark contrast to the background for 25-seconds (*Figure 7A*). To establish the baseline values for dynamic image learning, the participants were asked to view a rotating die presented as a 25-second long animation (without sound) (*Figure 7B*).

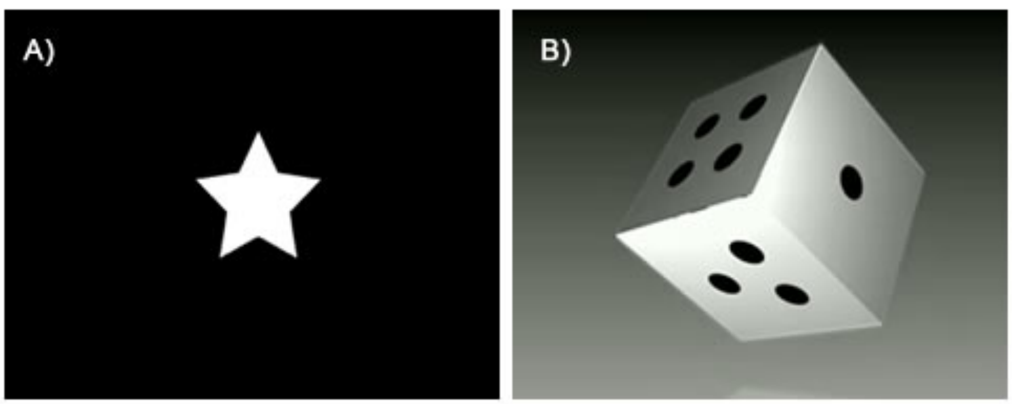


Figure 7. Baseline Procedure Images – Image A is the static baseline test. Image B is a rotating die that established baseline values for dynamic learning.

Cerebral blood (flow) velocity of the right MCA was measured in a sitting position using a 2-MHz pulsed transcranial Doppler ultrasound probe (Neurovision system, Multigon Industries, Elmsford, CA, USA). Finger arterial blood pressure (BP) was measured continuously and the brachial waveform (Finometer, Finapres Medical Systems BV, Amsterdam, The Netherlands) was corrected to brachial sphygmomanometric values. End-tidal CO_2 ($etCO_2$) was calibrated for atmospheric air pressure and measured (CAPSTAR 100, IITC Life Science Inc. Woodland Hills, CA. USA) using a mask. All collected data was collected using a data acquisition device (PowerLab 16/35, ADInstruments Inc. Colorado Springs, CO USA), and analyzed using analysis software (*LabChart*, ADInstruments Inc. Colorado Springs, CO USA).

Physiological measures and test performance measures, along with perceived mental effort scores were collected simultaneously. Participants completed learning tasks sitting in an upright position using a MacBook pro laptop to access the tests and learning resources. During this testing, participants had a CO_2 mask over their mouth and nose. A CO_2 analyzer collected end-tidal CO_2 concentrations. Further, a blood-pressure cuff was placed over the left arm of the participant, along with a finger cuff to measure blood pressure. The final apparatus to be attached to the participant was the TCD probe. Using a transduction solution, the probe was attached over the right temporal area of the participant. The right middle cerebral artery was located using audio and visual data from the Multigon console, as well as the output from *LabChart*. Identification of the MCA was determined by comparing values to the blood flow velocity obtained from prior research (Aaslid et al., 1982; Kelley et al., 1992; Stroobant & Vingerhoets, 2000), the signal pattern recorded on *LabChart*, and sound.

Once the location of the MCA was determined, baseline velocities were recorded in a random sequence. That is, the baseline for static learning or dynamic learning preceded the presentation of either the static or dynamic models respectively. Following the baseline physiological measures, the testing portion of the session was conducted. The order of modality, static or dynamic, was randomized. The participant was presented with a static or dynamic model to observe and study for 2 minutes. During this learning period, physiological variables were collected, and the investigator recorded observations. Following the learning cycle, the multiple choice style tests for the model just learned were presented. The tests were not timed, and participants were not forced to make decisions within a specified amount of time. After every two questions, participants rated their level of perceived mental effort on the prior question on a 9-point Likert scale (Brünken et al., 2010).

After one model had been learned and the tests for that model had been completed, the participant was asked to relax for a couple of minutes before the next baseline measure, learning phase and test cycle. In both static and dynamic learning conditions the tests were administered in the same manner. That is, participants were asked to evaluate their perceived mental effort after every two questions.

When the tests were completed, the investigator spoke informally with the participants about their experience during the session. This was not a scripted interview with standard questions. The intent was to compare the responses with the observations that the investigator had collected during the testing session. None of the participants were reluctant to answer questions or speak about their experiences.

3.9 Data Analysis and Synthesis

Quantitative data for the present study was collected using two pieces of software, *Sakai CLE* (LMS), and *LabChart*. *Sakai* recorded and tracked the test responses and subjective rating measures during the testing portion of the sessions. *LabChart* was used to compile all of the physiological variables that were collected during each testing session.

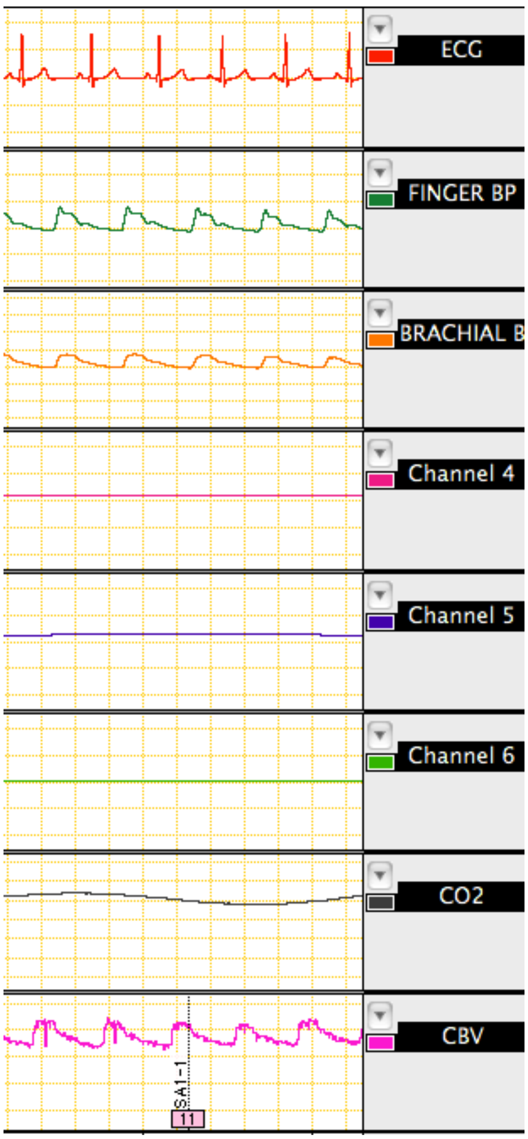


Figure 8 Description of Data Collection within *LabChart*: The image to the left is a screenshot of the *LabChart* display. The channels of interest for the present study are the CO_2 channel (second from the bottom) records the end-tidal CO_2 concentration (mmHg) of the participant. Finally, the CBV channel (bottom of screen) measures the mean cerebral blood velocity (cm/s). During the start of each question or learning phase a comment was added to the recorded data. This is indicated in the CBV channel by the 'SA1-1' and dashed line. This enabled the researcher to collect the mean values from all channels for each question. It also provided a fairly accurate measure of how long the participant spent on each question.

Figure 8. *LabChart* Screenshot Showing Data Collected

Once the session had ended, and the data had been collected and saved, it was exported to a *Microsoft Excel* sheet for organization and compilation with the results collected from the LMS. Importantly, not all continuous data was used in the analysis of this study. In order to collect appropriate timed sections, the data from *LabChart* were highlighted and mean values were reported (See *Figure 9*).

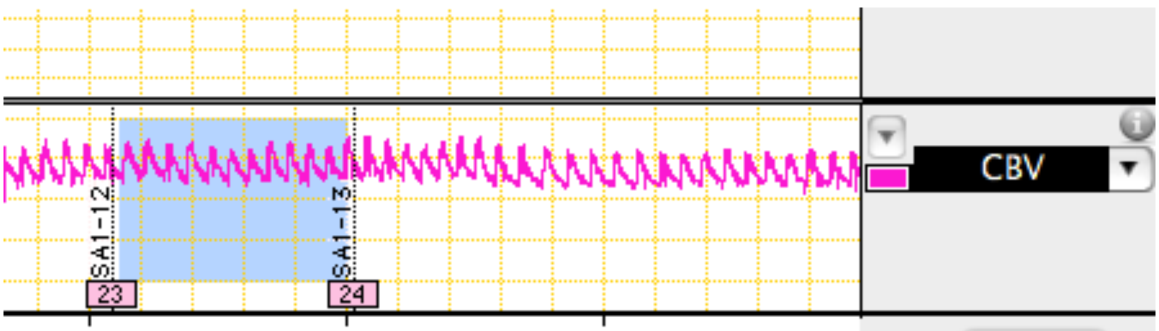


Figure 9. Highlighting Data in *LabChart* for Collection and Organization

Occasionally, noise or signal interference was an issue during data collection. In these instances the noise pops (indicated by the arrow in *Figure 10* below) were avoided during the collection process as described above (*Figure 9*). Since the region represented an average of the cerebral blood velocity, omission of noise signal would not impact the true average, and inclusion would have a drastic impact on the true signal.

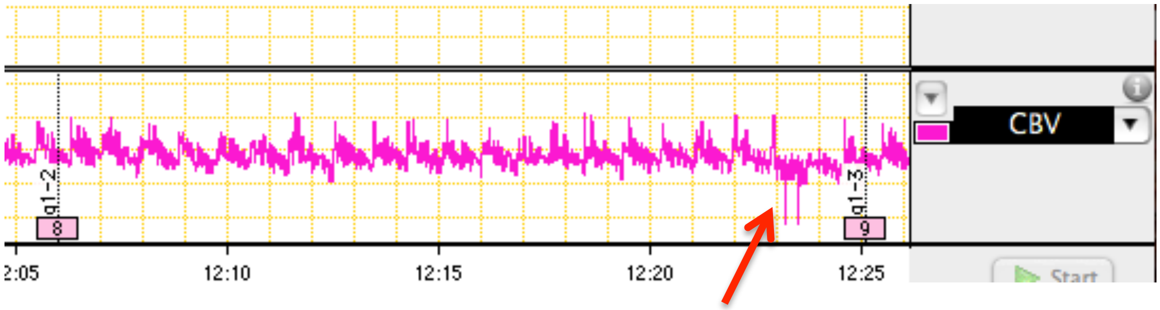


Figure 10. Signal noise displayed in CBV channel of *LabChart*

After the data was collected, it was compiled in *Microsoft Excel* for organization and later statistical analysis. Before statistical analysis, the researcher reviewed each individual's testing session and collected the time values for each question. This was done in the same manner as described above. Time values were collected by highlighting the region between each comment marker (See 'q1-2' to 'q1-3' in *Figure 10* above). These values were subsequently added to the spreadsheet with all physiological variables and test responses. The final product for each participant was a spreadsheet with all physiological values, performance results, perceived mental effort responses, and time taken to answer each question during the testing session.

3.10 Statistical Analysis

The present investigation aims to draw comparisons between participants with high and low spatial ability. An Analysis of Variance (ANOVA) comparing the overall mean percent change in cerebral blood velocity (CBV) between high spatial ability learners and low spatial ability learners was conducted to determine if CBV changed according to spatial ability, learning modality, and response accuracy.

A Pearson correlation was calculated to determine the relationship between perceived mental effort and mean percent change in CBV in high and low spatial learners. This analysis will determine the extent of any relationship between perceived effort and cerebral blood flow demands.

Finally, a compilation of the observational data provided for each of the groups enabled an item analysis of the field notes to determine if there are similarities within the groups and how this may be manifested by the collected quantitative measures.

3.11 Ethical Considerations

The experimental protocol for the present investigation was reviewed and approved by the Ethical Review Board at both the degree granting institution (University of Calgary), as well as the institution where the research was conducted (Western University). This section will highlight the standards that were required for completion of this study.

3.12 Issues of Trustworthiness

Previous research has provided guidelines to ensure that the results obtained during testing, such as mean CBV, and end-tidal CO_2, fell within reasonable limits (Aaslid et al., 1982; Bakker et al., 2014; Deppe et al., 2004; Hartje et al., 1994; Kelley et al., 1992; Mergeche et al., 2014; Stroobant & Vingerhoets, 2000). Since participants served as their own within subject comparison, idiosyncrasies in physiological variables were mitigated.

Half of the test instruments had been used in previous research and were shown to be effective (Nguyen, 2012; Nguyen et al., 2012). Further, the test used for the categorical variable of spatial ability has been validated and used in several previous studies (Mayer, 2010a; Mayer, 2014a; Meijer & van den Broek, 2010; Nguyen, 2012; Nguyen et al., 2012; Peters et al., 1995). The newly created test (e.g. ankle test) for the present study was designed in the same fashion as the other instrument that was employed; the spatial anatomy test (Nguyen et al., 2012).

Finally, the instrument used for measuring perceived mental effort was modeled on instruments used in previous cognitive load research (Angeli, Valanides, & Kirschner, 2009; Brunken et al., 2003; Brünken et al., 2010; DeLeeuw & Mayer, 2008b). Participants were asked to determine their perceived mental effort based on a nine-point Likert scale, where 9 was the highest level of exertion, and 1 was the lowest level of perceived exertion.

Overall, the test conditions were organized such that the modality of learning and testing were administered in a randomized fashion. Further, the tests were designed such that there were very close similarities in the questions to ensure internal consistency (Kline, 2013).

3.13 Delimitations and Limitations of the Study

3.13.1 Delimitations

The delimitations of the present study are related to the population and the material used in this investigation. Participants used in this study were typically upper year students with an inherent interest in anatomy or physiology. As a result, their motivation is likely greater than students in non-related disciplines. This motivation might limit the generalizability of the results obtained.

A further delimitation derives from the material used in this study. In an attempt to limit the variables and focus on one modality, the material used for this study was purely visual. There was no auditory component to the content presented during testing and learning. This means the cognitive load of one channel is being studied (Mayer et al., 2005; Mayer & Moreno, 1998, 2002). While it is anticipated that the addition of audio material would further exacerbate the affects of cognitive load, the present study aimed to limit and control the number of variables to study one mode of delivery. Perhaps further addition of audio material will be done in a later study.

3.13.2 Limitations

This study had several limitations that might impact the applicability of results to a wider audience. First, the use of transcranial Doppler ultrasonography for investigating visual processing limits research participants to right-handed dominant individuals. The lateralization and localization of neural functioning is very consistent and robust in right-handed dominant individuals. It is greatly dispersed in left-handed dominant individuals (Oldfield, 1971). As a result the left-handed dominant participants were excluded from the physiological testing in the present study.

A further limitation results from the nature of physiological variables. Idiosyncratic differences in blood pressure (MAP) and release of CO_2 make it difficult to categorize participants in the same fashion as high and low spatial ability. Therefore, changes that were observed were within subject changes. This helped to minimize the variability in physiological variables related to gender, age, and physical health.

Within the present study there was not a great disparity in mental rotations scores amongst the high and low spatial ability groups. This lack of disparity makes it difficult to determine the extent of variations in physiological variables in extreme high and low spatially able learners. There were not enough participants at the extreme ends of the spectrum in the present study to conduct any meaningful analysis that may help to predict the extent of differences in CBV of very high and very low spatial ability learners.

Finally, the use of various instruments to measure physiological responses to learning modifies the normal learning environment. Learners typically do not study or take tests with heart monitors, blood pressure cuffs and ultrasound probes attached to their body. While less invasive than other means to study changes in the brain, these instruments may have indirectly affected the level of physiological variables and even performance on the tests that were administered.

3.14 Methodological Issues and Challenges

The present research overcame several obstacles during the course of data collection. These will be highlighted here as they influenced the protocol and eventual research strategy.

The first issue was recruitment. Participants were primarily sought from large undergraduate classes where it was anticipated interest in participation would be high. Many undergraduates in science programs or ‘pre-medical’ science programs have little exposure to the broad and ranging applications of research beyond the professional school. Recruitment was welcomed, as this would expose students to other types of research within basic science, psychology and education. In spite of this, recruitment was a struggle. Roughly 33% of the individuals who had expressed interest in participation followed through with part one of the study (e.g. the mental rotations task). From this group of respondents, roughly half followed through with completion of the entire study (n = 33). The high attrition rate in respondents is believed to be due to the overwhelming amount of requests received by students for participation in research studies. Western University is a large research-intensive university with many opportunities for students to participate as research subjects. Since no compensation was provided for participation, the incentive for participation was purely left to intrinsic motivation. The recruitment was eventually broadened to include any learner who satisfied the criteria for participation. For this reason, the age range of the participant sample increased and more individuals with advanced degrees were included in study. Prior knowledge or advanced degree designation has been identified in the foregoing, and did not seem to offer any deviation from prior research findings (Nguyen, 2012; Nguyen et al., 2012).

The researcher spent considerable time learning how to calibrate and setup the research equipment for testing sessions. A fellow doctoral student who was intimately more familiar with the equipment, protocols and idiosyncrasies provided training. During the earlier phases of data collection several calibration errors and omissions occurred. In some cases (4 participants), the data was not usable. In other cases (3 participants) calibrations occurred after the fact within *LabChart* and the data was recovered and usable. The total number of complete data sets that were deemed usable was 29, as reported in previous sections. .

3.15 Summary

The foregoing section outlined the process and procedures for collecting data for the present study. Further, issues related to trustworthiness and ethical considerations were also presented. Adhering to previous research protocols and standards helped to mitigate these issues. The limitations and delimitations were presented as to identify and narrow the scope of the present study. The primary limitation of this study is the disruption of the natural learning environment. While the research took cautionary steps to minimize the confounding influence of the instruments used, these are still much less invasive than other means to study physiological changes in individuals during learning. Regardless of this, none of the participants indicated that these instruments affected their ability to concentrate or potentially learn during the testing sessions.

Chapter Four: **ANALYSIS AND RESULTS**

4.1 Introduction

The present study is an amalgamation of understandings from three different disciplines - anatomy, physiology, and education. Variables from each of these disciplines were selected and synthesized to provide data that would answer the research questions presented within this dissertation. This chapter provides an analysis of data and results to address the research questions presented earlier in this dissertation. The goal of this chapter is to summarize findings that will be elaborated on in the discussion and interpretation section presented in chapter five of this dissertation.

4.2 Demographics

The sample used for the following study was comprised of 29 healthy, right-hand dominant individuals with a mean age of (29 years ± 8.8) ranging in age from 18 to 51 years. There were 10 female participants and 19 male participants. *Figure 11* demonstrates the distribution of the sexes across high and low spatial ability. Mean mental rotation test scores for the high and low spatial ability groups were (16.4 ± 1.92 and 10.3 ± 2.65) respectively.

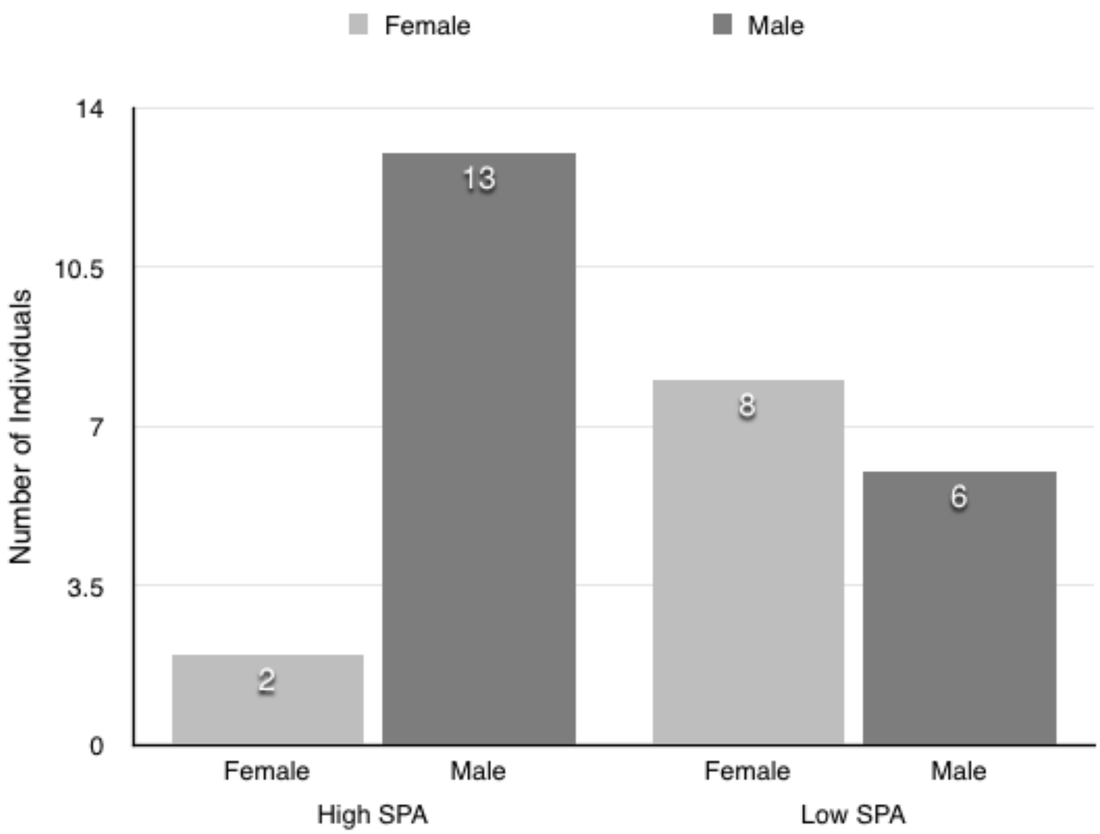


Figure 11. Distribution of Participants by Sex and Spatial Ability

The present study used 6 different tests to acquire data for analysis purposes. The results of these tests are presented below based on spatial ability groups (See *Figure 12*).

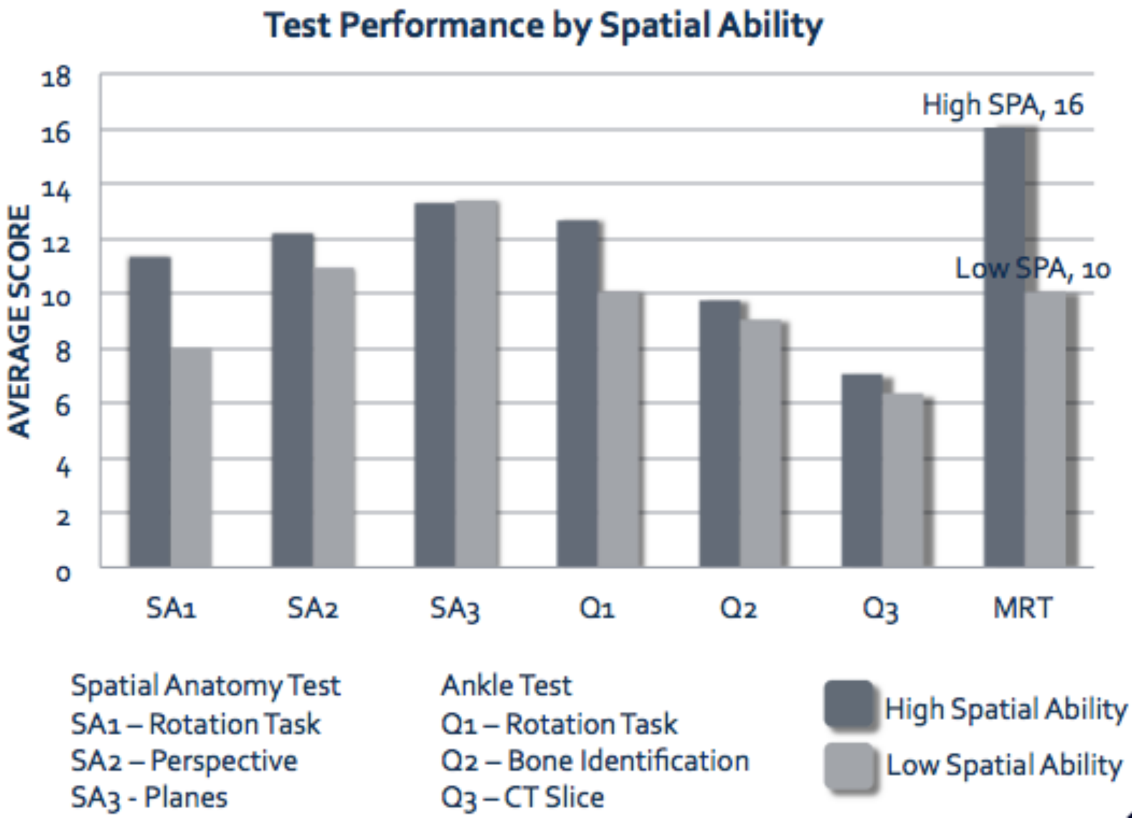


Figure 12. Comparison of test performance results by spatial ability groups

Figure 12 shows that overall performance was better for those in the high spatial ability group, excluding one test (SA3) where the low spatial ability participants marginally out performed the high spatial group. The remainder of this chapter will examine the variables underlying these results to determine the extent of any relationships between performance and physiological measures.

To further illustrate the argument that spatial ability is related to performance, a correlation between each participant's mental rotation test score and performance on the experimental tests for the present study was conducted. The results are presented in *Figure 13*.

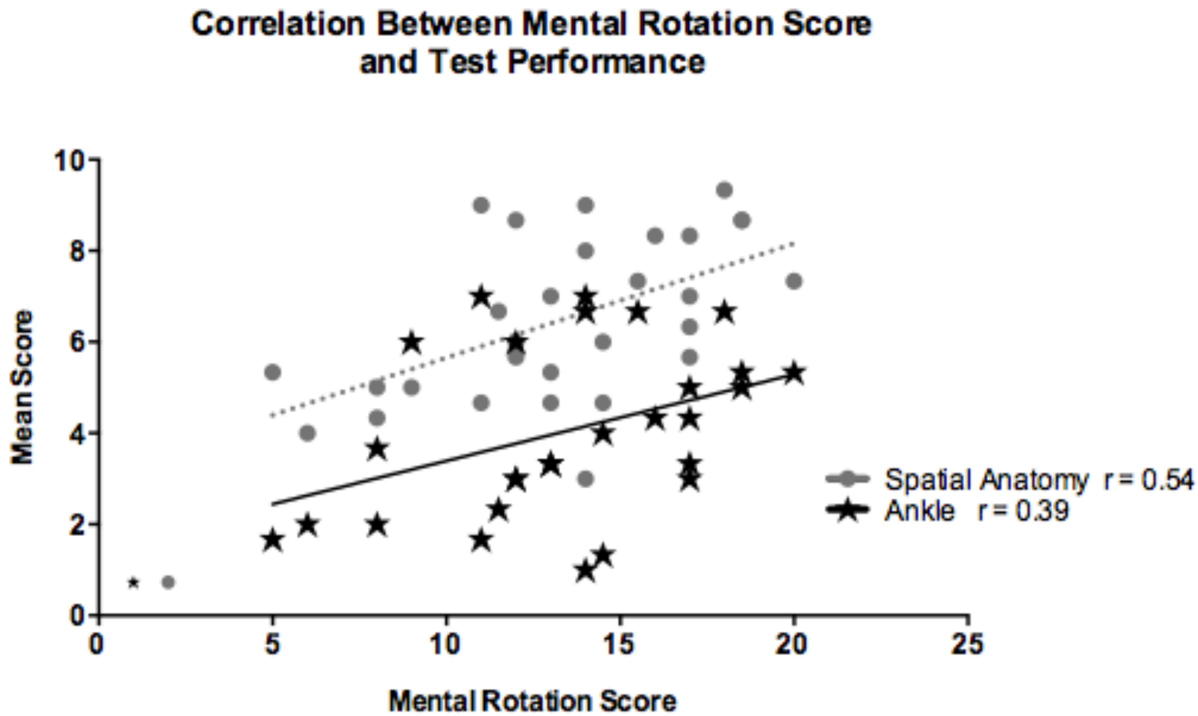


Figure 13. Correlation between spatial ability and performance

The results in *Figure 13* show that in both the Spatial Anatomy Test (SAT) and the Human Ankle Test (HAT), performance on post learning modality testing was positively correlated with the individual's spatial ability. Analysis of the HAT revealed a nearly strong positive correlation ($r = 0.39$, $p < 0.05$). A similar analysis of the SAT revealed a slightly stronger relationship ($r = 0.54$, $p < 0.005$). In comparison of performance on the two tests, the results suggest that learners performed significantly better on the SAT compared to the HAT, $t(56) = 5.197$.

4.3 Research Questions and Supporting Data

The primary goal of the present research was to determine the relationship between three measures; spatial ability, physiological changes resulting from learning, and the impact on performance. These variables are not easy to examine in isolation. Further, it is hard to measure one variable without influencing the others. For this reason, the research questions for the present study were primarily interested in the extent of these relationships. The data collected to answer the research questions for the present dissertation are presented below.

As mentioned in previous sections, prior CLT research utilizes rating scales of perceived mental effort or exertion. The present study examined the relationship between these measures, and physiological data. The rating scale for the present study was a 9-point Likert rating scale where 1 was low mental effort, and 9 was high mental effort. *Table 9* below highlights the important result that the perceived mental effort between the two spatial ability groups did not differ significantly $t(851) = 1.34$. Therefore, there is no distinction between spatial ability and the difficulty ratings provided by the participants. It is possible that the differences between high and low spatial ability groups could be exaggerated with an increased sample size.

Table 9. Mean Perceived Mental Effort by Spatial Ability Group

Group	Mean Perceived Mental Effort
High Spatial Ability	5.92 ± 1.7
Low Spatial Ability	5.75 ± 2

When the perceived ratings were separated by performance, a universal pattern emerged. *Figure 14* shows that incorrect responses were deemed to be more difficult in both high and low spatial groups. Conversely, questions that were answered correctly were rated as less mentally demanding. The differences between the groups were determined using a one-way analysis of variance. The results were found to be statistically significant [$F(3, 536) = 8.74$, $p < 0.0001$].

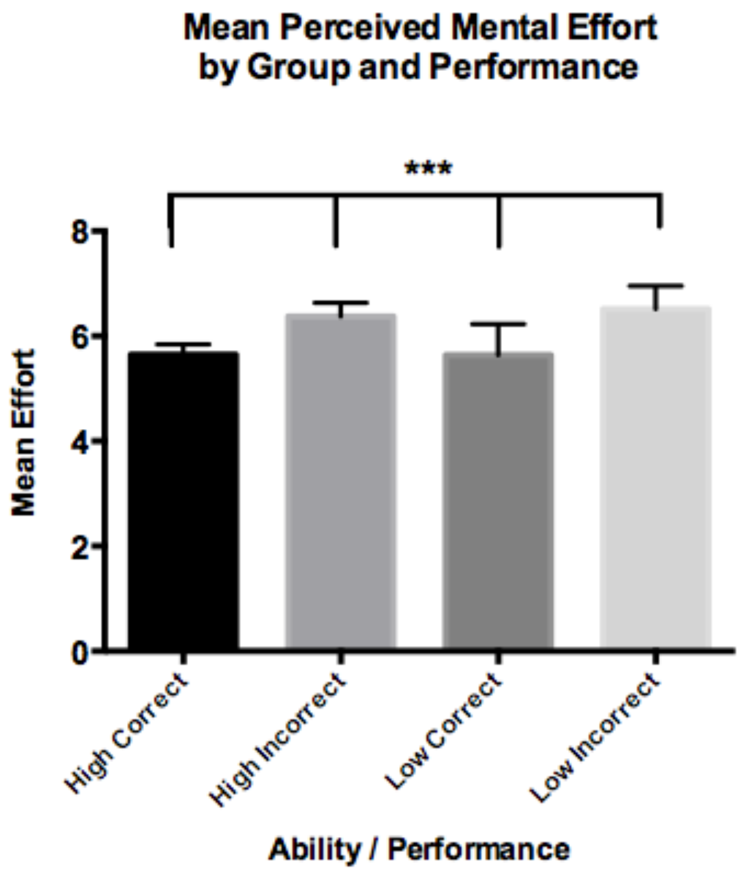


Figure 14. Perceived mental effort by group and performance

As stated above, one of the overarching questions for the present study was determining the relationship between perceived mental effort and how this may be manifested in a physiological response. *Figure 15* illustrates this relationship as a weak positive relationship ($r = 0.05$, $p < 0.05$) between perceived mental effort and percent changes in mean CBV in high spatial learners.

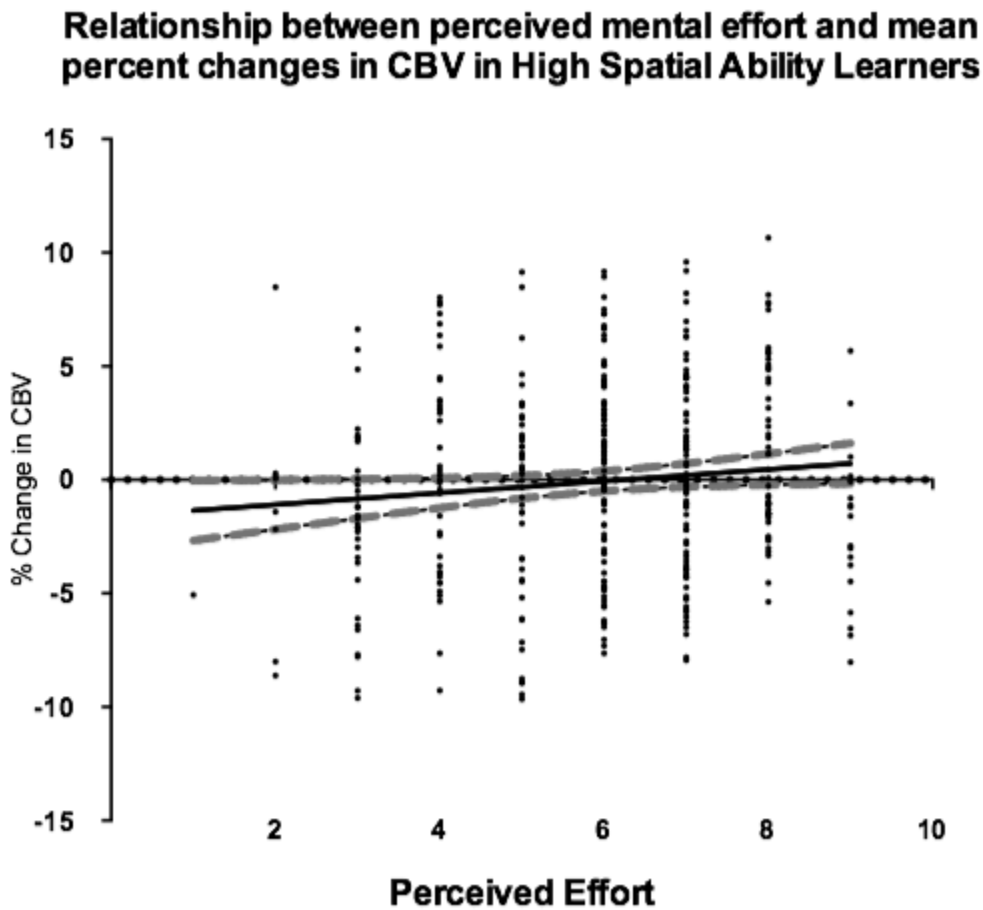


Figure 15. Results from Correlation of Perceived Effort and CBV in High Spatial Learners

Conversely low spatial ability learners (*Figure 16*) demonstrated the opposite relationship ($r = -0.12$. $p < 0.05$). The differences in directionality of the relationship between perceived mental effort and changes in percent CBV suggest that there is an effect occurring. However, the effect is not very strong likely due to factors like sample size and sensitivity of the rating scale.

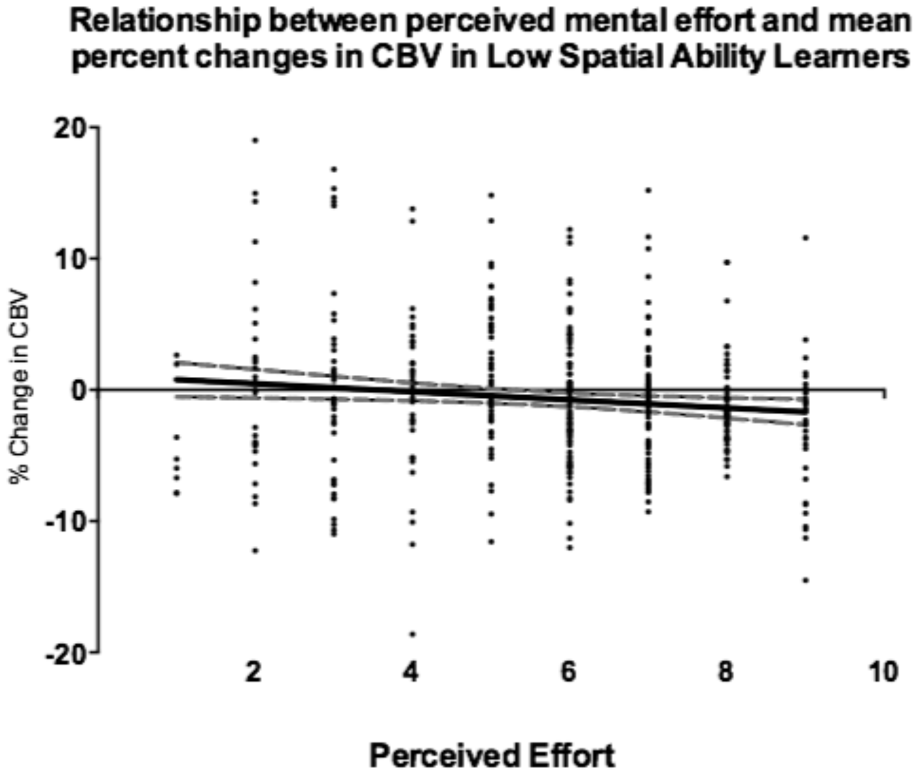


Figure 16. Results from Correlation of Perceived Effort and CBV in Low Spatial Learners

When correlations are sorted by ability, modality and correctness, there is no significant relationships (all $p > 0.05$) that result from perceived mental effort and changes in percent CBV (See *Table 10*).

Table 10. Correlation matrix for CBV and perceived effort, modality, spatial ability and performance.

	High Spatial Ability	Low Spatial Ability
Dynamic Correct	r = 0.09	r = -0.134
Dynamic Incorrect	r = -0.203	r = -0.168
Static Correct	r = 0.129	r = -0.04
Static Incorrect	r = 0.305	r = -0.175

In spite of the weak relationships presented in *Table 10*, it should be noted that there is a pattern that has emerged with respect to directionality. That is, all of the low spatial ability relationships point to negative correlations, and all but one of the high spatial ability relationships are positively correlated. This will be discussed in further detail in chapter 5.

To determine the extent of the physiological changes within participants, baseline values for the mean CBV were taken prior to each learning task. The mean baseline values for the spatial ability groups and modalities of delivery are presented in *Table 11*.

Table 11. Baseline CBV values by Ability and Modality

	Static Baseline	Dynamic Baseline
High Spatial Ability	64.1 ± 5.1cm/s	64.3 ± 8.1cm/s
Low Spatial Ability	62.1 ± 10.3cm/s	63.1 ± 11.2cm/s

To measure the significance of the difference between the baselines of the modalities within each spatial ability group, a t-test was conducted. There is no significant difference between static and dynamic baseline CBV values in high spatial ability participants $t(887) = 0.34$. Similarly, there was not significant difference between the static and dynamic baseline of the low spatial ability group, $t(950) = 1.54$. This comparison helps to emphasize the results obtained during the testing phase of the study. *Figure 17* highlights the changes that occurred in CBV during the learning tasks based on ability, modality and performance.

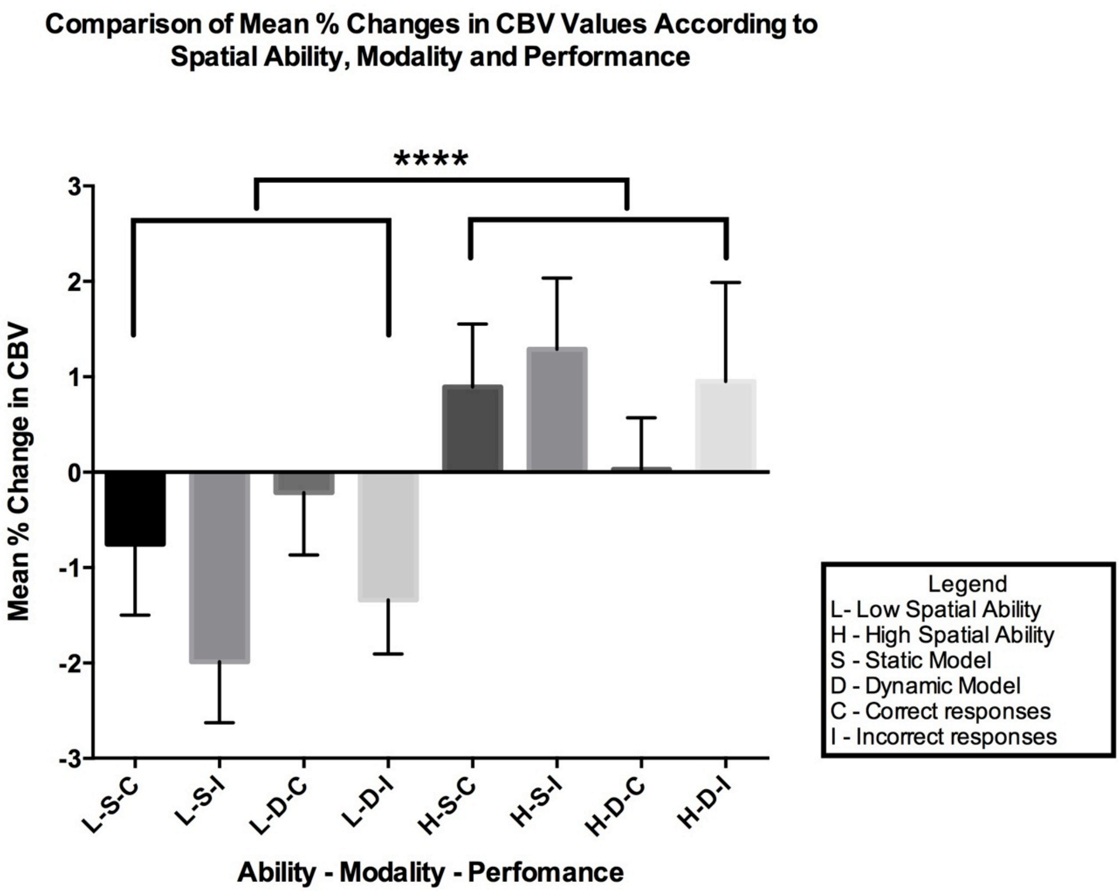


Figure 17. Comparison of Mean Percent Changes of CBV based on Ability, Modality, and Performance.

A one-way ANOVA was used to determine if there was a significant difference in mean percent change in CBV values based on learner ability, the modality of delivery and performance. The results (*Figure 17)* show that there is a difference between groups, but not within groups [$F(7, 1651) = 10.41$, $p < 0.0001$]. *Table 12* below highlights where these specific significant differences occur between groups. It appears that modality has a greater impact on the individual, than performance. This is indicated by the level of significance in the static (S) compared to the dynamic (D) models in the low (L) spatial ability participants.

Table 12. Significance table for mean percent CBV changes between participant categories

	H-S-C	H-S-I	H-D-C	H-D-I
L-S-C	**	**	ns	*
L-S-I	****	****	***	****
L-D-C	ns	ns	ns	ns
L-D-I	****	****	ns	***

Note: ns $p > 0.05$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$, **** $p \leq 0.0001$

L = Low spatial ability, H = High spatial ability, S = Static Image, D = Dynamic Image, I = Incorrect Response, C = Correct Response.

To ensure the measures of cognitive processing were the result of changing demands for oxygen in the brain, and not other factors like stress, the end-tidal CO_2 (etCO_2) of each participant was monitored during the course of testing. This is a standard transcranial Doppler study (TCD) practice that has been highlighted throughout the literature (See Cupini et al. (1996); (Duschek & Schandry, 2003; Kelley et al., 1992; Mergeche et al., 2014; Stroobant et al., 2008)).

Again, as with CBV, $etCO_2$ was analyzed by a within subjects comparison of changes. The mean baselines by spatial ability and modality are presented in *Table 13* below. To compare the means of the static and dynamic baseline within each spatial ability group, a t-test was performed. The results of the t-test suggest that there is no significant difference between the baseline $etCO_2$ values of static or dynamic modalities in high spatial ability learners, $t(85) = 1.38$. Similarly, there is no significant difference between the static and dynamic condition in low spatial ability participants $t(91) = 0.90$

Table 13. Mean $etCO_2$ baseline values by ability and modality

	Static Baseline	Dynamic Baseline
High Spatial Ability	35.1±10.5 mmHg	33.5±10.7mmHg
Low Spatial Ability	30±12.6 mmHg	29.9±13.1mmHg

The $etCO_2$ baseline values above further emphasize the results obtained during the testing conditions. *Figure 18* below shows the change in $etCO_2$ values based on spatial ability, with no significant difference based on modality or performance.

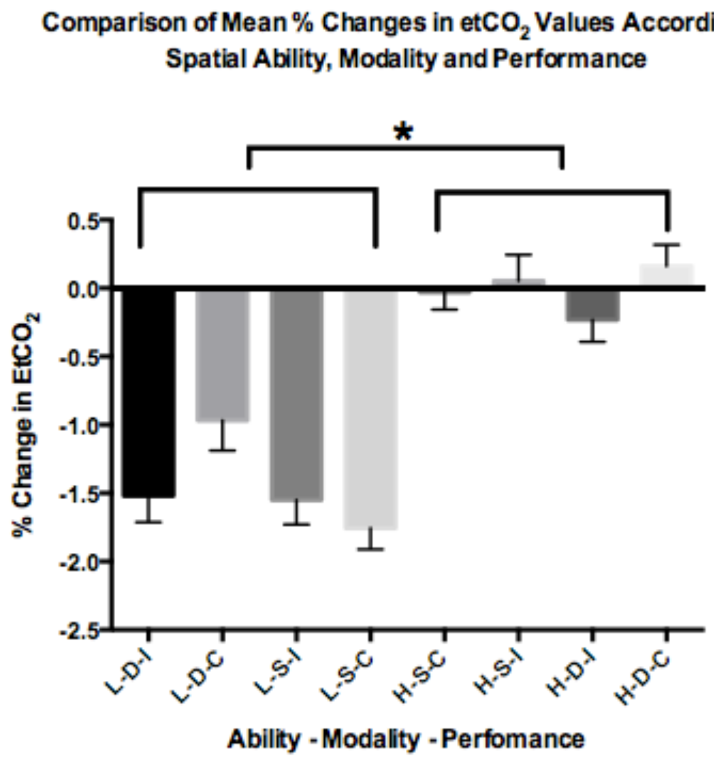


Figure 18. Comparison of End-Tidal CO_2 amongst categories of participants

Comparison of mean percent changes in $etCO_2$ between high and low spatial ability learners was conducted using a one-way ANOVA. The results indicate a difference between groups [$F(7, 1659) = 22.59$, $p < 0.0001$], but not within groups across modality of learning and accuracy (correct vs. incorrect responses). *Table 14* below highlights where these specific significant differences occur between groups.

Table 14. Significance table for end-tidal CO_2 values between participant categories

	H-S-C	H-S-I	H-D-C	H-D-I
L-S-C	****	**	*	****
L-S-I	****	****	***	****
L-D-C	**	**	****	ns
L-D-I	****	****	****	****

Note: ns $p > 0.05$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$, **** $p \leq 0.0001$

L = Low spatial ability, H = High spatial ability, S = Static Image, D = Dynamic Image, I = Incorrect Response, C = Correct Response.

The above results are critical for explaining other factors that may be contributing to the changes in the dependent variable for the present study (CBV). This will be discussed in further detail in the chapter 5 of this dissertation.

Figure 19 highlights the mean percent differences in CBV when learners of different spatial abilities learn with either static or dynamic images.

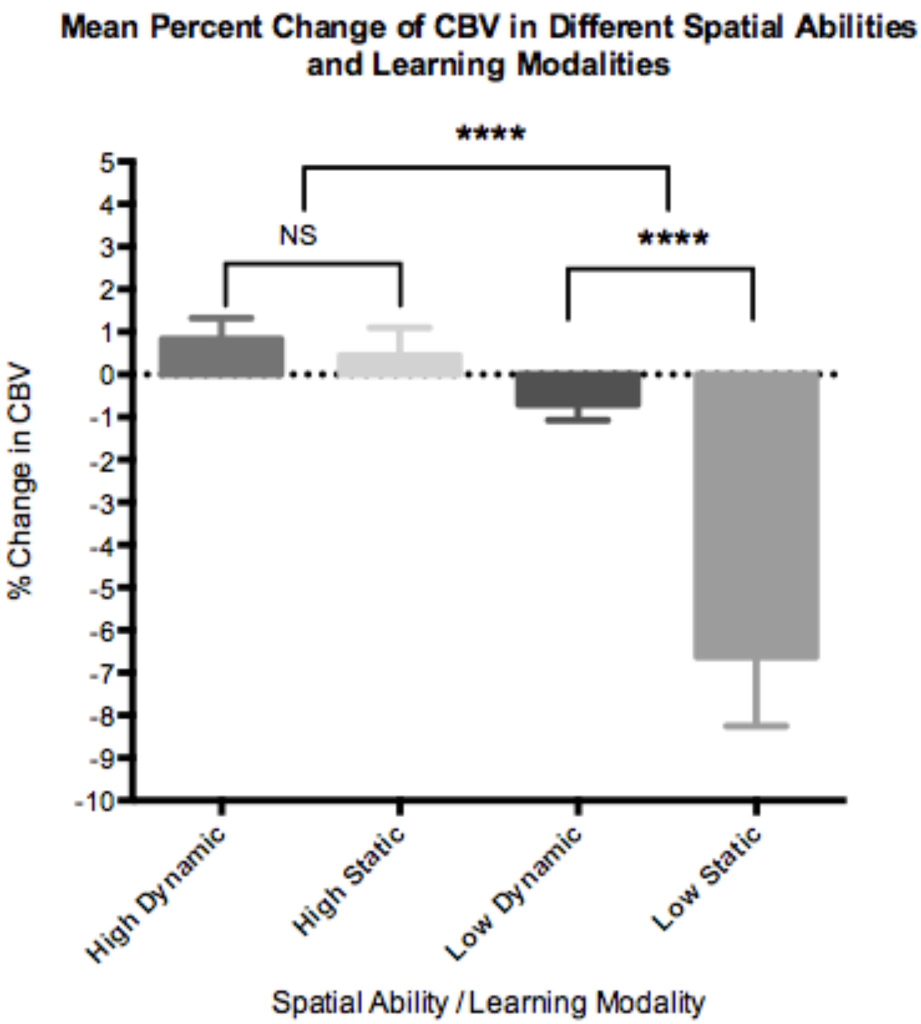


Figure 19. Comparison of Mean Percent Changes in CBV during learning with Static or Dynamic Images in High and Low Spatial Ability Groups

The above results suggest that there is a significant difference in cognitive processing of image types according to spatial ability ($p < 0.0001$). Further, these results also suggest that lower spatially able participants had a significant difference in processing image type ($F(3,2604)$ =

55.36, $p < 0.0001$), where as there was no significant difference in learning with either image in the high spatial ability group.

To help ensure that the changes that were being obtained were the result of cognitive processing and not external variables like stress, the end-tidal CO_2 values were recorded during the testing procedures. The results from $etCO_2$ are displayed in *Figure 20*.

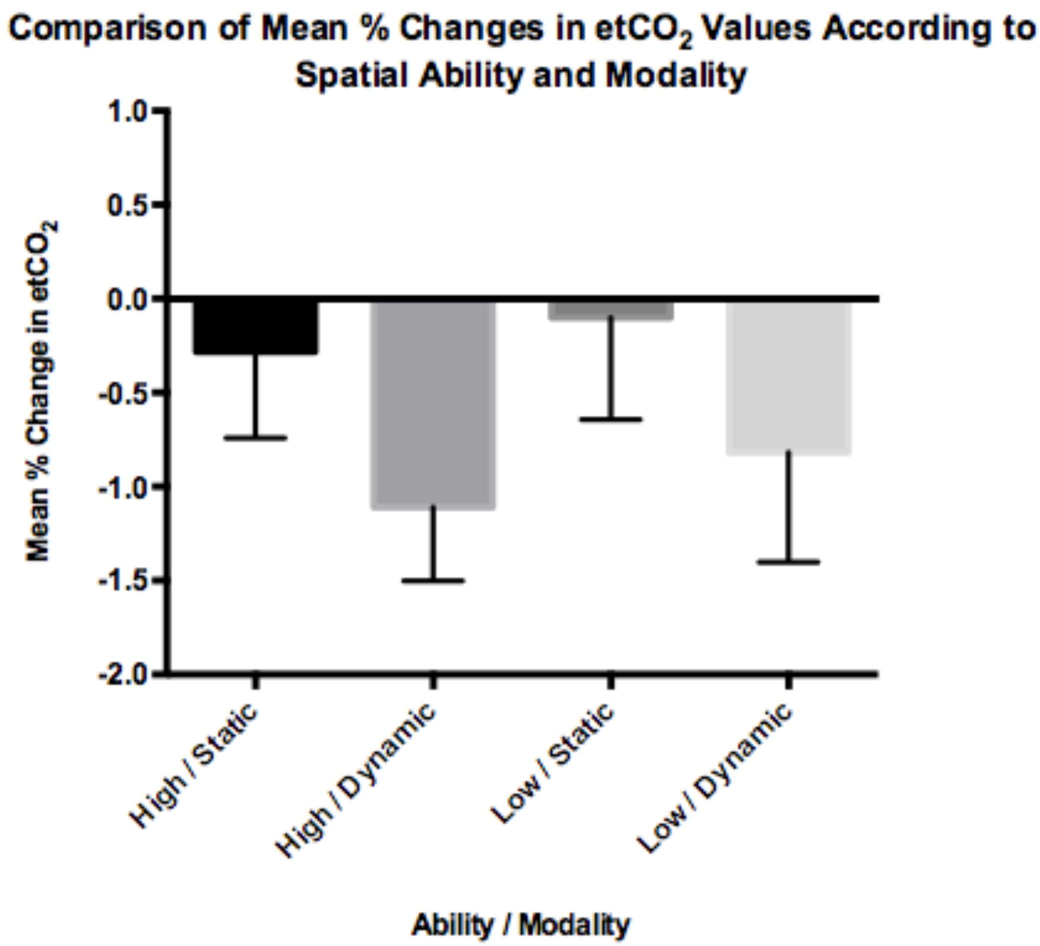


Figure 20. Comparison of $etCO_2$ values based on ability and modality categories

In spite of the uniformity in image type displayed above in *Figure 20*, results from a one-way ANOVA showed no statistically significant difference exists [$F(3,176) = 0.874$, $p > 0.05$] between modality and ability when examining $etCO_2$ values. Therefore it can be assumed that the measures derived from the CBV portion are related to cognitive processing and not dramatic changes in respiration. This result will be discussed in further detail in chapter five.

In terms of arterial pressure, which may influence CBV, there was no difference between the modalities, static and dynamic, in high or low spatial ability groups, [$F(3, 36) = 2.704$, $p > 0.05$].

Table 15. Average baseline values for Mean Arterial Pressure (MAP) by ability and modality

	Static Baseline	Dynamic Baseline
High Spatial Ability	95.5±13.4 mmHg	98.5±12 mmHg
Low Spatial Ability	113.3±16.9 mmHg	108.8±18.3 mmHg

4.4 Summary of Quantitative Results

Given the limitations described in the foregoing, particular statistical analyses such as a multivariate analysis of variance (MANOVA) were not feasible to determine what variable had the greatest affect on CBV. To conclude that the proper interaction and relationships can be drawn from the collected data, a generalized linear model (estimating equations) was calculated. Spatial ability, age, gender and performance were independent variables, and mean percent change in CBV was the dependent variable in the model. The result of this test suggested that the strongest predictor of changes in mean percent CBV was spatial ability ($p < 0.05$) (See *Table 16*).

Table 16. Generalized Linear Model (Estimating Equations) Effect

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	.025	1	.875
High_Low	4.579	1	.032
Score	.017	1	.896
High_Low * Score	1.920	1	.166

Dependent Variable: CBV_Change
Model: (Intercept), High_Low, Score, High_Low * Score

4.5 Follow-Up Data

Observational data for the present study was collected as field notes. Data was collected using various instruments that were amalgamated into *LabChart*. The researcher observed the progress of the participants during testing to mark the beginning and ending points of questions. This observation formed the basis of question analysis data from a physiological perspective. During this process, the researcher took notes on changes that were taking place within the participants. For example, did the participant seemed rushed or confused? How did this behaviour appear to affect their CBV readings? Further, patterns in question response behaviours were observed, such as speed of response repetition of answer selections. As one participant had suggested, "there was no penalty for incorrect responses, and I was just trying to complete the tasks".

Following the testing phase, the researcher engaged in an unstructured interview with each of the participants. The researcher asked the participant about their experiences and which tests they thought were the most difficult. The researcher was careful not to influence the responses of the individuals by asking specifics regarding the tests or which mode or presentation was preferred. Responses from the participants were collected and organized in a table once the participants had left the testing area. Notes were also taken on data collection tracking sheets that were also added to the table for thematic analysis.

A review of the field observations recorded during the testing sessions yielded several themes with regards to the spatial ability groups. The most predominant themes were related to ability and memory. Specifically, higher spatial learners seem to rely on their skills more. For example, during dynamic learning the CBV values for high spatial ability learners did not spike or fluctuate as drastically as lower spatial ability participants. It was like they could anticipate where images were going to move. Further, their troubles with the tests were about 'confusion' and rarely did they mention issues with memory. Lower spatial learners seem to rely more on memory to help with their responses. It appears that they attempted to remember the location of bones. This became difficult when the questions presented structures in more obscure perspectives (i.e. with skin on the ankle). Further, the chief complaint of low spatial learners was a lack of memory for locating structures.

In both high and low spatial groups, participants commented that the images were confusing and the provided cues seem to be more of a distraction rather than a support for their learning. This theme was more pronounced in the ankle model where there were more elements for the learner to consider (i.e. the seven tarsus bones, compared to three tube structures). Conversely, cues for the spatial anatomy test are incorporated into the question (i.e. easy to eliminate incorrect responses). Cues that did help learners, such as elimination of structures in the SAT, appeared to help low spatial learners more than high spatial learners as indicated in test SA3 performance (See *Figure 12*).

4.6 Unexpected Findings

As mentioned in the foregoing, $etCO_2$ was measured as a means to ensure that the CBV values obtained were the result of cognitive processing and not related to changes in respiratory patterns. Changes in breathing patterns between the high and low spatial ability groups were observed (See *Figure 20* above), and there was no difference found between spatial ability groups and modality of learning. When the end-tidal CO_2 values were separated by correct and incorrect responses in both static and dynamic modalities and by spatial ability groups (See *Figure 18* above), a difference was obtained. It appears that lower spatial ability participants hyperventilate slightly compared to their high spatial ability counterparts. This is indicated by the decrease in end-tidal CO_2 values across all conditions. This measure was used as a mechanism to ensure that changes in CBV were not being influenced by changes in breathing. However, this may be a variable to examine in future iterations of the present research.

4.7 Summary

The results from the present study have supported the hypotheses and have provided answers to the research questions as posed. While the strength of the relationships is not strong, the findings are statistically significant. With possible changes in data collection methods, and an increased sample size, it is possible that these results may become more dramatic. Regardless, the present study has provided some evidence to support the contention that learners with different spatial abilities handle different media types in different ways and this has a measurable impact on their cognitive processing and ability to learn.

Chapter Five: **DISCUSSION**

5.1 Introduction

Several years ago, Stanley Katz, the director for Arts and Cultural Policy at Princeton University wrote an article for *The Chronicle of Higher Education* regarding emergence of information technology in education. The article can be encapsulated by the quote, ‘don’t mistake a tool for a goal’ (Katz, 2001). Educational technology often focuses on the development and implementation of tools, rather than looking at the physiological impact of these tools on the learner and learning outcomes. The present study examined the direct impact of a general technological innovation (digital media) on learners and cognitive processing. The goal of the present study was to determine how the use of multimedia resources impacts changes in cerebral blood velocity (CBV) and subsequent learner performance. Results from the present study have highlighted several important elements for consideration in the fields of education, educational technology and the learning sciences. This research was an attempt to address the impact of learning with digital media using methods and tools from different disciplines, namely physiology and neuroscience. Presented within this chapter are the interpretations of the results and a discussion of future directions that may help to further elucidate some of the unanswered or unresolved issues that remain from the present study.

5.2 Discussion and Interpretation

For several decades neurologists and neurophysiologists were able to make the connection between cerebral hemodynamics and cognition (Raichle, 2001a). Through the work of researchers like Mosso and Sherrington in the late 19th century (Raichle, 2001a), to more recent studies in the latter part of the 20th century, and early 21st century (Aaslid et al., 1982; Kelley et al., 1992; Raichle, 2001a; Stroobant & Vingerhoets, 2000), the relationship between cognitive processing and the requirement for oxygen, carried by blood to the brain is well established. One question that is not fully addressed is the relationship between physiological response, perceived mental effort and learner performance during non-verbal learning tasks using spatially complex digital images (Charlot, Tzourio, Zilbovicius, Mazoyer, & Denis, 1992). The present study attempted to make a connection between learning, the perception of mental effort and the relationship to cerebral blood flow as a primary physiological response.

The results from the present research support earlier findings that indicated that individuals with higher spatial ability perform better than lower spatial ability learners on visual tasks (Meijer & van den Broek, 2010; Nguyen, 2012; Nguyen et al., 2012). These results are more profound when complex images are used as a learning tool Khalil et al. (2005b); (Lowe, 2004; Lowe, 1999). The data presented within this research shows that there are distinct physiological differences pertaining to spatial ability during learning with complex visual learning objects.

The focus of the present study was on changes in cerebral blood velocity (CBV), a surrogate to cerebral blood flow measures within the right Middle Cerebral Artery (rMCA) of the brain during different learning scenarios using static and dynamic images. Learners were categorized as high or low spatially able depending on their relative standing following the completion of the standardized mental rotations task (Peters et al., 1995). Since spatial ability is deemed to be a limiting factor in using complex images effectively (Garg et al., 1999b), the categorization served as a method for comparison purposes. Additionally, as stated in chapter two the focus on the rMCA was undertaken as prior research identified the rMCA as the primary artery responsible for perfusion of the regions of the brain responsible for interpreting visual information (Stroobant & Vingerhoets, 2000).

The results from the present study demonstrate that differences between high and low spatial ability learners exist not only in terms of test performance but also physiological response. High spatial ability learners experience a small increase in mean CBV from baseline during all learning conditions; static and dynamic tasks, correct or incorrect responses (see *Figure 16*). Conversely, lower spatial ability learners had decreased mean CBV values across the same learning conditions (See *Figure 16*). Drastic changes in the variables like CBV, heart rate, and end-tidal CO_2 have implications for physiological factors like fainting or syncope. Therefore, the differences between groups were not anticipated to be drastic.

There are several possible interpretations for the obtained findings. Previous functional magnetic resonance imaging (fMRI) research has shown that the prefrontal cortex (PFC) is a critical region for working memory (Aizenstein et al., 2004; Barrett et al., 2003; Bunge, Ochsner, Desmond, Glover, & Gabrieli, 2001; Chao & Knight, 1995; D'Esposito, 2007; Thomason et al., 2009). It was suggested that the PFC would become more active in response to tasks where the learner was required to rely on their working memory (Thomason et al., 2009). For fMRI studies, active regions are denoted by an increase in signal intensity of brain areas due to changes in metabolism. This phenomenon is referred to as the Blood Oxygen Level Dependent (BOLD) signal, where MRI scanners are able to detect changes in electron resonance due to cellular metabolism, or the requirement for oxygen (McRobbie et al., 2010). As stated earlier, lower spatial ability learners likely relied more on memory to successfully complete the current learning tasks. Therefore, the reliance on memory to complete the learning tasks as reported by lower spatial ability participants would allow one to speculate that CBV is changing in the other regions of the brain. This assumption is due to previously reported fMRI data (Thomason et al., 2009) . Several studies have shown that blood flow for working memory of spatial tasks is greater in the frontal and prefrontal cortex, an area of the brain perfused primarily by the anterior cerebral artery (ACA) (Prabhakaran, Narayanan, Zhao, & Gabrieli, 2000; Rypma, Prabhakaran, Desmond, Glover, & Gabrieli, 1999). Therefore, since an individuals overall blood volume does not change, one could speculate that the drop in CBV in the rMCA may be the result of blood flow shunting to other areas of the brain such as the anterior cerebral artery (ACA), or less likely in the posterior cerebral artery (PCA).

The finding that CBV in the rMCA of high spatial ability learners increases, compared to lower spatial ability learners suggests that spatial ability enables the brain to increase processing, and thus metabolism, in the regions required for spatial reasoning. This has been referred to as the concept of cognitive efficiency (Hoffman, 2012; Hoffman, McCrudden, Schraw, & Hartley, 2008), where cognitive processing is presumed to be more focused or localized. Conversely, in lower spatial ability learners, the localization of processing is not as focused and more brain regions become active (D'Esposito, 2007; D'Esposito, Postle, & Rypma, 2000; Small & Duff, 2008). To confirm this hypothesis alternative methods would be required for testing. This will be addressed later in this chapter.

When comparing mental effort to changes in CBV, the results are not as clear but do offer some evidence to explore explanations. Classically, subjective rating techniques have been used as the primary tool for evaluating cognitive load. Paas, Ayres, and Pachman (2008) wrote that, ”although self-ratings may appear questionable, it has been constantly demonstrated that people are quite capable of giving a numerical indication of their perceived mental burden” (p. 18). Interestingly, although there were differences between high and low spatial ability learners in CBV levels, there were no corresponding differences in the overall mean of self-reported exertion between high and low spatial ability groups (See *Table 9*).

When a correlation analysis was conducted to measure the relationship between perceived mental effort and changes in CBV, it was discovered that although a weak relationship existed, high and low spatial ability learners differed in the direction of their relationships. In the high spatial learner group, the relationship between perceived mental effort and mean percent CBV changes was positive but very weak. Conversely, the lower spatial ability group demonstrated a negative correlation of mental effort versus changes in CBV from baseline values. Despite the strength, the relationships demonstrate the directionality of the correlations is novel, not currently explored in the literature. Furthermore, this interaction of spatial ability and brain metabolism related to blood flow warrants further attention. Higher spatial ability participants evaluated their perceived mental effort higher when their mean percent CBV increased. This indicates an awareness exerting more effort and conforms to previous results reported in the educational literature that learning requires effort. Lewalter (2003) found that successful learners were aware of the cognitive demands of using either static or dynamic images. Lewalter (2003) suggested that learners used organization strategies to assist their comprehension of material. Static images required more intense effort compared to dynamic images. This was believed to occur because dynamic visuals reduce complexity of material, and organize the sequence of events requiring less planning and organizing compared to static images.

In contrast to the high spatial ability result, lower spatial ability learners demonstrated a negative relationship, whereby they evaluated questions easier when mean CBV values rose. This suggests that lower spatial ability learners interpreted questions as being easier when blood velocity had increased in the rMCA. Alternatively, increases in CBV within other arteries may be occurring while the mean CBV within the rMCA appears to be decreasing. Therefore, the assumption is not that lower spatial ability learners have diminished cognitive processing during easier questions. Rather, processing is not occurring with the same intensity as high spatial ability learners in the region perfused by the rMCA(Charlot et al., 1992).

When looking at the outcomes of the Lewalter (2003) study, it is important to note that this study examined the use of static and dynamic visuals to explain the optical phenomenon of an astrophysical concept, the doubling of a star. In contrast, the present study used complex images to convey the spatial relationships of an anatomical model. The differences in the present study and Lewalter (2003) study show another important aspect of using images for instructional purposes. The nature of the content does have an impact on the types of images we use to convey information and concepts. Images are used to help illustrate concepts or highlight relationships to reduce intrinsic load. The present study shows that images for certain concepts might only be beneficial for learners with high spatial ability. Lewalter (2003) showed that images used to depict an astrophysical concept were effective when the learner was able to plan and organize material in a meaningful manner. This is a critical aspect of CLT where germane load or generative processing is increased to help learning (Van Merrienboer et al., 2006; van Merrienboer & Sweller, 2010). Germane load requires more effort and possibly more cognitive processing. Presently, we are unable to determine the discrete elements of cognitive load theory in terms of effort or processing. Like the relationship between learning and memory, it is likely that extraneous load, intrinsic load and germane load occur simultaneously or within close temporal proximity making distinctions difficult or impossible.

The results of the correlation analysis do offer promise for future investigations examining the relationship between mental effort and cognitive processing. At present the relationships presented here are not strong. A possible explanation for the relatively weak correlations between spatial ability and mean percent changes in CBV may be due to the relatively low disparity in spatial ability found within the subject pool of the present study. It is possible that more extreme differences in spatial ability could result in more profound differences in CBV and perceived mental effort. Unfortunately, there were not enough participants at the extreme ends of the spatial ability spectrum to conduct a meaningful test of this hypothesis.

5.3 Relationship of the current study to previous research

Clark and Clark (2010) wrote about the need to investigate CLT, stating the importance of biological, physiological and neuroscience research. They suggested, ‘two important problems must be addressed before we can advance much further with CLT are that we have not yet found an unobtrusive and reliable way to measure cognitive load and we need to determine whether any specific source of cognitive load is productive for individual learners during instruction’ (p.208). The results of the current study link biological and self reported indices of mental effort and link them to innate skills like spatial ability in a short-term learning study.

As stated in the foregoing chapters of this dissertation, extraneous load is concerned primarily with the presentation of material and is believed to impose demands on cognitive processing. Further, germane cognitive load is considered to be cognitive processing that contributes to learning and is caused by challenging or motivating the learner to exert effort towards understanding material (Mayer & Moreno, 2010a). The present research investigated the extraneous and germane load components of CLT using a relatively unobtrusive method from physiology, while juxtaposing this with commonly used instruments for measuring CLT; self-reporting measures. Clark and Clark (2010) suggest that 'self-reporting measures appear to be confounded with personal judgements about the difficulty of the task rather than the amount of mental effort invested' (p. 208). For this reason, it was anticipated that the physiological data would complement the self-rating judgements of mental effort and present a more comprehensive snapshot of learner behaviour while interacting with digital learning objects like those employed in the present study.

The present study is unique in the field of CLT research and addresses a gap in the literature. Several research articles have suggested the necessary instrument to measure changes in cognitive processing is fMRI (Clark & Clark, 2010; Whelan, 2007) but this dissertation proposes an alternative. The use of fMRI for CLT research may be premature as the technology is used primarily for mapping localizations of active regions during cognitive processing (Cabeza & Nyberg, 2000). The data from fMRI studies is more profoundly interested in location (spatial), rather than processing (temporal) data (Ashby, 2011). Since CLT is concerned with processing and the limitations of our cognitive capacity, it was more prudent to use TCD for the present study. Transcranial Doppler ultrasound is non-invasive like fMRI but relatively unobtrusive and is much more sensitive to temporal changes in the demand for blood within the brain during cognitive tasks.

Although the nature of cognitive load could be addressed with fMRI, it addresses slightly different questions than those addressed with TCD. Functional magnetic resonance imaging will enable researchers to show relative changes in the activity of brain regions (Small, Moody, Siddarth, & Bookheimer, 2009b). However, knowledge of discrete cortical regional activity may be misleading, as cognitive load is not a discretely defined construct. That is, the cortical areas subtending the three aspects of cognitive load; extraneous load, intrinsic load, and germane load may not be consistent, and may well vary depending on the cognitive task at hand. Whelan (2007) made the assumption that regional activation would be indicative of a specific aspect of CLT, based on findings from the research literature. Whelan (2007) suggested the dorsolateral prefrontal cortex is the region responsible for intrinsic processing, the posterior parietal association cortex is the region responsible for extraneous processing, and the superior frontal sulcus and intraparietal sulcus are the regions responsible for germane processing. The problem with this speculation is that it has been pieced together from various unrelated research. The cognitive tasks from these research studies were not consistent, and many of the conclusions were derived from animal studies. This type of theorizing has not been critically evaluated. Within the educational literature, proponents of brain-based learning have welcomed articles like Whelan's (2007), as it attempts to bridge the gap between basic neuroscience research and educational research (Bruer, 1997; Dekker et al., 2012). This will be discussed in greater detail later in the present chapter.

Other measures like pupil dilation and vascular constriction have been used as an attempt to put a physiological meaning to cognitive load (Brünken et al., 2010; Clark & Clark, 2010). Pupil dilation is directly related to increased activation of the sympathetic nervous system, sometimes referred to as the "fight or flight" aspect of the autonomic nervous system. Pupillary dilation increases proportionally with mental workload, and with task familiarity though repetition, pupil diameter decreases, suggesting easing mental exertion or demand (Clark & Clark, 2010). Vascular constriction and mental effort have a similar relationship to the pupils, as the controlling factor is the sympathetic nervous system. Iani, Gopher, and Lavie (2004) demonstrated that constriction of arteries in the finger is a measure of sympathetic nervous system activation that could be used as a measure of mental effort. Thus, indices of pupillary and sympathetic nervous system responsiveness may be promising, but are based on secondary physiological responses rather than directly measuring blood flow related events linked to cognitive processing vis-à-vis TCD or fMRI.

Transcranial Doppler ultrasonography of the large basal vessels like the middle cerebral artery (MCA) in the current study has a more direct relationship with processing in the brain. Stroobant and Vingerhoets (2000) reported several studies where TCD was used to monitor blood flow changes during cognitive tasks. Unlike other methods like pupil dilation or vascular constriction TCD is typically used in concert other measures to ensure that the changes that are being observed are the result of cognitive processing and not some other factor that could influence constriction of blood vessels, such as changes in respiration as reflected in the $etCO_2$ or the blood pressures recordings made in the current study. For this reason, TCD appears to be a suitable methodological approach that could be added to future investigations of cognitive load. As mentioned earlier, changes to blood flow irrigation territories is probable between individuals of differing spatial ability, it is hypothesized that blood flow to the anterior cerebral artery is likely occurring in lower spatial ability learners. Transcranial Doppler ultrasonography may not be a suitable method for testing this hypothesis as the Doppler signal to measure the CBV of the MCA and ACA could not be conducted simultaneously. The physical size of the probe prevents closer proximity but perhaps more importantly, signal interference between the two probes would occur as the MCA and ACA are in relatively close proximity. Therefore, the necessary method to test this hypothesis would be functional imaging.

5.4 Implications of the Present Study

The results of the present study will have implications for professional practice and decision-making, understanding of cognitive load for the field of educational technology, theory building and future research. These will be discussed in sequence below.

The data for the present study provides evidence that spatial ability helps to mitigate the effects of cognitive load when learning with different types of images. These results offer some evidence in order to aid decision-making when implementing technological tools for instruction, especially for visual disciplines like anatomy and other STEM related disciplines. Lowe (2004) suggested that the implementation of visuals for learning is outpacing adequate research to show how these impact cognitive processing capabilities of learners. The present study focused primarily on one aspect of images; static or dynamic. This was done so that identification of effects could be limited to the image type itself and not due to the effects of additional media (e.g. audio); controls and elements that may further exacerbate the effects of extraneous load (Mayer, 2014a; Sanchez & Wiley, 2006). The answer obtained from the present study is straightforward, high spatial ability learners are able to use all image types, static or dynamic, effectively. Conversely, lower spatial ability learners have difficulties with more complex images. Further, it should be noted that spatial ability does not diminish the necessary effort required for learning (Lewalter, 2003). Evidence for this was provided by changes in CBV between the high and low spatial ability groups. Spatial ability seems to help learners handle image type more effectively.

Educational professionals should be aware that there are limitations to the tools used for instructional purposes. For example, Vorstenbosch, Klaassen, Kooloos, Bolhuis, and Laan (2013) found that image selection had an impact on the learning outcomes in anatomy, and they concluded that spatial ability was a critical variable for successful learning outcomes in anatomy. Knowing that spatial ability is a limiting factor for success in learning of certain disciplines, it may be feasible to provide remedial assistance in the form of training to help make these tools useful for all learners (Huk, 2006; Lubinski, 2010; Meijer & van den Broek, 2010). Meijer and van den Broek (2010) found that lower spatial ability learners benefitted from the opportunity to explore more when using complex images. Further, others have suggested that remedial spatial ability training may help to improve this skill in students (Huk, 2006; Lubinski, 2010), but this has not been tested to determine if this training helps students learn with complex images. Remedial training of skills like spatial ability is somewhat speculative. The relationship between training a skill and generalized increase in intelligence has been criticized as a neuromyth (Dekker et al., 2012). The present study offers a mechanism to determine if changes are occurring, as changes in CBV could be suggestive of an effect resulting from remediation.

The results from the present study will add to our understanding of cognitive load, and potentially revise the theory. Cognitive load is a theoretical construct that makes assumptions about underlying cognitive processes. However, cognitive load is difficult to study since the elements of cognitive load likely do not occur in isolation of one another. That is, it is difficult to study the impact of extraneous load in isolation of intrinsic load or germane load. These elements of cognitive load likely work simultaneously. Regardless, theorists often make assumptions about cognitive processing due to cognitive load without measuring brain processes in any direct manner (Clark & Clark, 2010). The results presented here show that cognitive load is not a universal construct, and it is mitigated by other factors like spatial ability. Our understanding of cognitive load may need to be widened to include necessary skills for learning as a means to reduce the burden of learning. Thus far, most of the suggestions for reducing cognitive load are typically generalized to instructional design aspects and the appropriate use of multimedia to support learning (Mayer, 2010a; Mayer & Moreno, 2010a; Mayer, 2014a; Schnotz & Kurschner, 2007; Sweller, 1993b; van Merrienboer & Sluijsmans, 2009).

There are some cautionary warnings with the present study. The present study has answered the question about the changes in CBV resulting from learning with different types images; comparing two groups of participants based on spatial ability. The results show that processing patterns are different amongst spatial ability groups, but the underlying reasons are presently left to speculation based on prior research findings. The present results should not be used as concrete evidence to support many of the assumptions perpetuated by brain-based learning proponents (Christodoulou & Gaab, 2009; Pasquinelli, 2012). For example, the results presented here do not provide evidence to support the notion of the left-brain, right-brain dichotomy where it is believed certain characteristics reside within specific hemispheres, and learners demonstrate certain characteristics due to hemispheric dominance (Bruer, 1997; Dekker et al., 2012; Goswami, 2006). This study focused on the rMCA because this is the artery responsible for perfusion of the region of the brain that processes visual information (Aaslid et al., 1982; Kelley et al., 1992; Stroobant & Vingerhoets, 2000). Further, as with many studies involving the brain, right hand dominance is preferred due to the predictability of lateralization of functions (Oldfield, 1971). Right hand dominance is not indicative of selection bias for left or right-brain characteristics as described above. Finally, these results and recommendations do not provide evidence to suggest that instructional interventions can purposefully activate specific brain regions to stimulate or enhance learning (Christodoulou & Gaab, 2009; Pasquinelli, 2012). The present study focused on a generalized region supplied by the rMCA. Other brain regions were also active during the learning tasks for the present study. Due to methodological constraints of using TCD, other arteries could not be simultaneously monitored to determine the extent of the changes.

This study offers an excellent starting point for further examination of neurophysiological tools in education research. Information processing theory (IPT) and cognitive load theory (CLT) have provided a solid theoretical lens to explain how learning occurs in humans (Driscoll, 2005; Ormrod, 1999; Schunk, 2012). This research offers a generalized look at cognitive processing by looking at the changes in blood velocity during learning. An analogy for the present study is watching vehicular traffic patterns. This study examined the speed of traffic using a ‘radar gun’ in the form of a Doppler probe. The purpose was to measure the changes in traffic flow. Future research may be more interested in determining where the traffic is going. This line of investigation would provide answers to the speculation that changes in low spatial learners are occurring because traffic in other arteries is increasing, while the rMCA traffic is slowing down. To accomplish this the shift in focus is more spatial than temporal, and the methods required would be fMRI (Whelan, 2007).

Other areas of potential interest may be derived from differences observed in $etCO_2$ as well as the qualitative data collected. Breathing patterns and self-reported ratings of anxiety may suggest that stress has a role in influencing cognitive processing in lower spatial ability learners. Stressors and self-perceived levels of stress have rarely been reported in the cognitive load literature related to learning. These are typically variables included in workload studies, which could be considered a derivative of cognitive load, as many of the demands are similar (Lichacz, 2005; Smith, Gevins, Brown, Karnik, & Du, 2001; Spinks, Zhang, Fox, Gao, & Tan, 2004).

Other skills and abilities should also be tested against cognitive load and perceived mental effort. One such ability is fluid reasoning (Prabhakaran, Smith, Desmond, Glover, & Gabrieli, 1997). Prabhakaran et al. (1997) showed that processing patterns for individuals with high fluid reasoning skills were more focal than those with poor fluid reasoning skills. This pattern is similar to what was found and hypothesized in the present study.

5.5 Recommendations

The recommendations derived from the present study are primarily directed at the implementation of technological tools for instructional purposes, rather than changes on how we view learning and cognitive load. The results from a study such as this could be misinterpreted within the education literature as has often been done when basic neuroscience encroaches into education research (Dekker et al., 2012; Goswami, 2006). These points will be discussed in sequence below.

Several schools of thought have presented recommendations for the design and development of education tools based on the concept of cognitive load (Chandler & Sweller, 1992; Dutke & Rinck, 2006; Hoffler & Leutner, 2007; Huk, 2006; Jamet & Le Bohec, 2007; Kalyuga et al., 1999; Kenny, 2009; Kirschner, 2002; Le Bohec & Jamet, 2005; Morrison & Anglin, 2005; Ozcinar, 2009b). Evidence to support this typically came from self-evaluation and measurement of learning outcomes (Brünken et al., 2010). Arguments to support these findings were based on theories about cognitive architectures and memory (Baddeley, 2003; Reed, 2006; Sweller et al., 1998). The present study has provided data to show that high spatial ability learners have a common pattern of processing information as indicated by increases of CBV in the rMCA. Conversely, lower spatial ability counterparts show a decline in CBV in the rMCA. At this time the reason for the discrepancy can only be speculated upon based on previous fMRI data. However, acknowledging there is a difference and showing that it has an effect on learner performance, instructional designers and instructors need to consider methods to assist lower spatial ability learners. One suggestion is to provide complex images, such as the dynamic models used in the present study, as still images from canonical views along with the dynamic model. Canonical views are typically still images taken from standard angles, such that comparison of two images is easier (Chandler, 2004). It is believed this recommendation would benefit those with lower spatial ability skills since the movement of the image appears to be the critical aspect having an impact on learning. Further, other research has shown that controls enabling lower spatial ability learners to stop and explore images have been beneficial for learning (Khalil et al., 2005a; Meijer & van den Broek, 2010).

It is important to examine the results presented here critically. This study was done with a relatively small number of participants looking at a single delivery modality; visual media. This research is a preamble to future studies where other media (i.e. audio) can be incorporated to determine the effects of multimedia learning on changes in mean CBV. The critical point here is that many factors impact cognitive processing and we are only able to understand them one at a time. Brain-based learning proponents often do not take this into consideration and try to define instructional principles based on results like those presented here (Bruer, 1997; Dekker et al., 2012; Goswami, 2006). The outcome of the present study is a clearer understanding of the complexity of human cognitive processing. While there appears to be differences in the processing capabilities of high and low spatial ability learners, there is no clear distinction in how these learners perceive mental effort or exertion. Therefore, cognitive load itself is not clearly defined in terms of physiological or self-rating methods. Finally, the present study and results highlight the difficulties of studying cognitive load. Cognitive load theory proposes that there are three elements that contribute to the total cognitive capacity of an individual; extraneous load, intrinsic load, and germane load. It is difficult to isolate each of these elements to determine how much they contribute to the total capacity, or how cognitive processing changes during each of these aspects of cognitive load. In the end, we can manipulate the input (extraneous load) and observe what occurs inside the 'black box' making assumptions based on the definitions of intrinsic and germane processing. The process of learning however likely does not occur in a piecemeal or stepwise fashion. Rather, the aspects of cognitive load likely blend together and occur simultaneously.

5.6 Summary

This study has provided some evidence to illustrate the importance of spatial ability for learning with different types of digital media. The differences in spatial ability seem to help mitigate the potential effects of cognitive load. However, measuring cognitive load is still a challenge. The present study attempted to show that cognitive load could be correlated with physiological variables to show that cognitive load is correlated with cognitive processing as measured by changes in mean CBV. This study will serve as a starting point for future studies using TCD as a method for evaluating cognitive load. Future studies can build upon the results and methods presented here by adding elements of complexity to instructional tools and observing the resultant changes in physiological variables like CBV and $etCO_2$. Further, the present study offers a mechanism to monitor changes in CBV if remediation of spatial ability is added to instruction.

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