AN EXAMINATION OF THE EFFECTS OF MATHEMATICS ANXIETY, MODALITY, AND LEARNER-CONTROL ON TEACHER CANDIDATES IN MULTIMEDIA LEARNING ENVIRONMENTS

by

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Abstract

This study examined mathematics anxiety among elementary teacher candidates, and to what extent it interacted with the modality principle under various degrees of learner-control. The experiment involved a sample of 186 elementary teacher candidates learning from eight versions of a computer program on division with fractions. The eight versions varied in modality of presentation (diagrams with narration, or diagrams with written text), control of pacing (pacing was controlled by either the learner or the system), and control of sequence (sequence was controlled by either the learner or the system). A pre-test, post-test, demographic questionnaire, subjective measure of mental effort, and the Abbreviated Math Anxiety Survey were also administered. This study revealed that mathematics anxiety was significantly positively correlated with mental effort, and significantly negatively correlated with engagement, pre-test and post-test scores. Additionally, a modality x pacing interaction was observed for both high prior knowledge and low mathematics-anxious students. Under system-pacing, the modality effect was observed, and these students achieved higher far transfer scores when learning from the diagrams and narration modality condition. However, under learner-pacing, the modality effect reversed, and high prior knowledge and low mathematics-anxious students performed better on far transfer scores when learning from the diagrams and written text modality condition. Low prior knowledge, and highly mathematics-anxious students performed poorly in all treatment conditions. Additional interactions involving sequence-control, and a four-way interaction involving prior knowledge, modality, sequence-control, and pacing were also uncovered. The results from this study demonstrate that prior knowledge and mathematics anxiety have a complex relationship

with the effectiveness of the format of instruction, and the design of instructional materials needs to take into account these individual differences of mathematics anxiety and prior knowledge.

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Chapter 1: Introduction

During the past two decades, developments in computer technology have significantly affected how information is conveyed in multimedia learning environments. Originally computer programs communicated messages through text alone; however, recent advances have enabled instructional designers to readily create computer programs that include images, text, sounds, animations, and video. With the emergence of the World Wide Web as a means for delivering e-learning materials, instructional designers now have an opportunity to increase both the interactivity and accessibility of multimedia programs. The resources available for creating effective, interactive, and easily accessible e-learning programs are now more abundant and affordable than ever. Nevertheless, the application of new technologies to the design of e-learning programs does not in itself guarantee a product that promotes efficient and deep learning. In order to maximize the potential positive impact that new computer technologies may have on learning, instructional designers need to understand how best to create multimedia programs that facilitate learning. Until recently, little was known about how combining images with words during instruction affected students' learning. However, researchers have now developed a set of evidence-based principles to guide the design of effective instructional multimedia programs. These principles are grounded in cognitive theories of learning, and they describe how and when to incorporate images with words in multimedia programs.

In this thesis, I will present a study designed to investigate whether one of these principles, the modality principle, can be utilized as a design guide in the context of an authentic and interactive e-learning environment. The modality principle has been developed over the past two decades from research showing students who learn from diagrams and concurrent spoken text produce significantly better learning outcomes than students who learn the same material from diagrams and written text (Leahy, Chandler & Sweller, 2003; Moreno & Mayer, 1999; Mousavi, Low & Sweller, 1995; Tindall-Ford, Chandler & Sweller, 1997). While there is sufficient evidence to support the robustness of this principle in certain well-defined and system-controlled e-learning environments, there still remains much research to be done in order to fully understand the circumstances under which the modality principle can facilitate learning in interactive learner-controlled multimedia learning environments.

This thesis begins with a rationale explaining the theoretical and evidential support for the modality principle in multimedia learning. Chapter 2 describes the purpose of this study in detail, and Chapter 3 outlines the methods chosen for data collection and analysis. The fourth chapter includes the results of the data analysis, and Chapter 5 completes this study with a discussion of the findings, which includes a section on limitations and future research.

Chapter 2: Literature Review

The modality principle is theoretically grounded in two cognitive theories of learning. Cognitive Load Theory (Paas, Renkl & Sweller, 2003; Sweller, 2005) and the Cognitive Theory of Multimedia Learning (Mayer, 2001, 2005) both posit that the modality effect occurs due to an overload of information being processed by the visual channel in working memory. By presenting information to both the visual and auditory channels, rather than just the visual channel, working memory capacity is expanded, and more resources can be allocated to the construction of schemas in long-term memory (Mousavi et al., 1995). The following sections further detail the two theories and how they support the modality principle.

Cognitive Load Theory

Cognitive Load Theory is based on specific ideas regarding the cognitive architecture of long-term memory, working memory, and certain learning mechanisms (Sweller & Chandler, 1994). More specifically, it explains how the limited capacity and duration of working memory influence the effectiveness of certain instructional designs (Pawley, Ayres, Cooper & Sweller, 2005).

According to Cognitive Load Theory, long-term memory consists of an unlimited number of schemas. Schemas are hierarchical information networks that enable learners to categorize several pieces of information as a single element. Schemas can be created or altered when new information is incorporated into the long-term memory. Once a particular schema has been constructed, it can be brought back to the working memory and treated as a single feature.

It has been well documented that working memory has both a limited capacity and a limited duration (Pawley et al., 2005). Previous experiments have demonstrated that working memory can hold only about four chunks of novel information for no more than a few seconds (Cowan, 2001). Consequently, when presented with new concepts to be learned, working memory can become easily overloaded. When the cognitive load on working memory is too high, learning is hindered.

Intrinsic, extraneous, and germane cognitive load are the three types of cognitive load explained by the Cognitive Load Theory. Intrinsic cognitive load is determined by the element interactivity of the information being processed. Information that is high in element interactivity must be understood simultaneously with other pieces of information. This increases the intrinsic cognitive load, and puts higher demands on the individual's cognitive resources, potentially leading to an overload in the working memory. Extraneous cognitive load is increased by instructional materials that ignore the limitations and architecture of working memory. First of all, learners can experience extraneous cognitive load when their cognitive resources are required to attend to information that is not essential for concept formation. This situation can overburden the working memory and lead to a cognitive overload. Secondly, extraneous cognitive load can occur when instructional materials ignore that working memory is comprised of multiple subsystems (Low & Sweller, 2005). Research has shown that working memory consists of at least two partially independent channels or memory stores (Baddeley, 1998; Clark & Paivio, 1991). The visual channel is responsible for processing incoming visual information, while the auditory channel processes auditory information presented to the learner. Since these two channels can process information somewhat independently (Baddeley), working memory capacity is maximized when instructional materials make use of both the visual and auditory channels. Since working memory is so limited in capacity and duration, it is imperative to design instructional materials that minimize extraneous cognitive load, thereby enabling cognitive resources to focus solely on learning the material and constructing the appropriate schemas in long-term memory. Finally, germane cognitive load deals with the cognitive effort required for schema acquisition and automation. This type of cognitive load is essential for effective learning (Sweller, 2005).

The total cognitive load on the working memory is equal to the sum of the three separate types of cognitive load. Therefore, if the intrinsic cognitive load is very high, extra care must be taken to reduce the extraneous cognitive load so as not to overburden the working memory.

Cognitive Theory of Multimedia Learning

As described in Mayer (2005), Cognitive Theory of Multimedia Learning (CTML) is based on three cognitive science principles of learning. The first principle states that humans possess separate channels for processing incoming visual and auditory information (Moreno & Mayer, 2000). Information in the form of illustrations, video, and on-screen text is initially processed by the visual/pictorial channel, while information in the form of narration or music is first processed in the auditory/verbal channel. The second principle, based on Sweller's Cognitive Load Theory (Chandler & Sweller, 1991), is that both of these channels have a limited capacity for processing information (Sweller, 1999). The third cognitive science principle states that humans engage in active learning by attending to new information and organizing and integrating it into their long-term memory (Moreno & Mayer).

The Cognitive Theory of Multimedia Learning specifies that there are three key processes that occur when attending to new information in a multimedia presentation (see Figure 1). The first phase of processing involves selecting relevant words and images from the multimedia presentation. When words are presented aurally, they enter the auditory channel; when words are presented as on-screen text, they are processed through the visual channel. Images enter through the visual channel. However, after the words

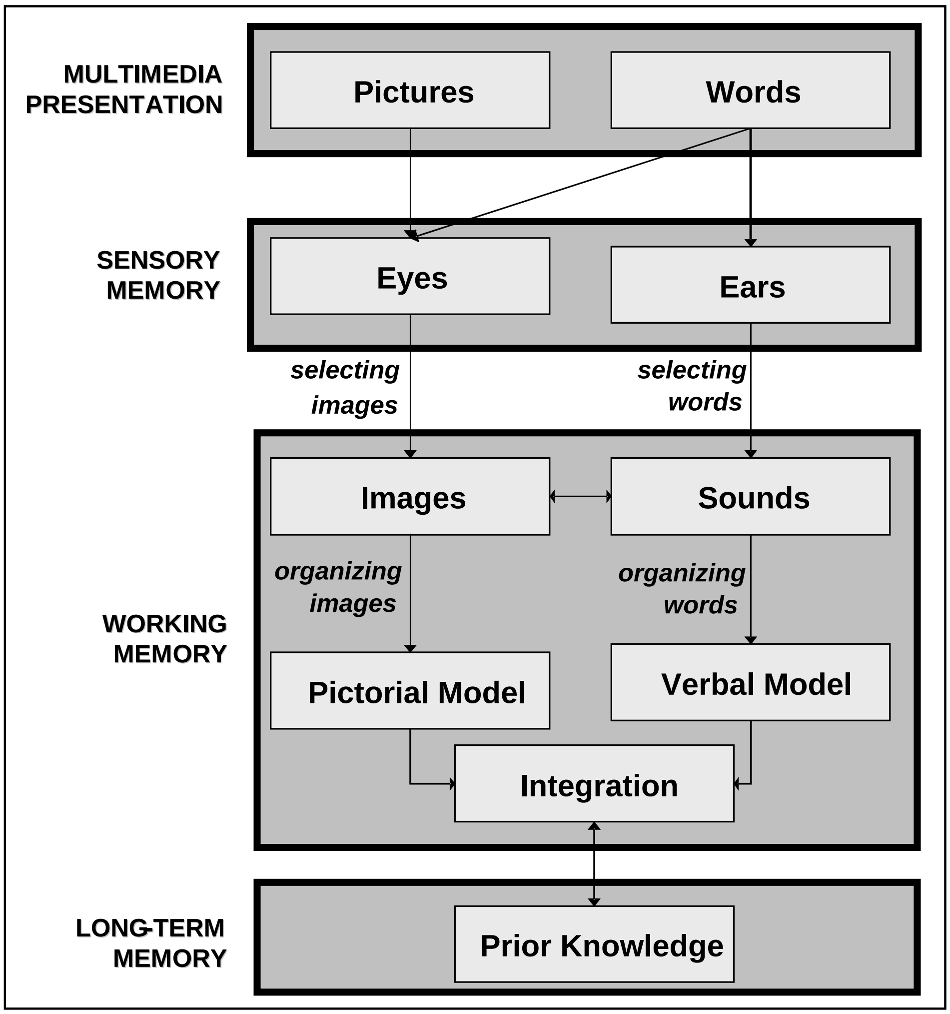

Figure 1. Pictorial representation of the three processes involved in the Cognitive Theory of Multimedia Learning. Adapted from Mayer (2005).

and images have been selected, they can switch channels. For example, on-screen text can be relocated to the auditory channel if the learner decides to mentally articulate the text. In the second phase of processing, words and images are organized into verbal and pictorial models. The models form coherent representations that help the learner make sense of the information. In the final stage of processing, the verbal and pictorial models are integrated with one another and connections are made between the integrated model and prior knowledge in long-term memory.

How Cognitive Theories Explain the Modality Principle

Cognitive Load Theory and the Cognitive Theory of Multimedia Learning provide similar explanations for the experimental conditions that produce the modality effect. The theories are based on the assumption that humans process incoming information in two separate channels or systems. One channel processes visual information and the other channel processes auditory information. When instructional materials are presented as diagrams and written text, the visual channel is responsible for processing all of the incoming information, while the auditory channel is left unused. If the material is high in element interactivity, the visual channel may become overloaded. As a result of the cognitive overload, very few resources will remain available to commit the information to long-term memory. However, if the instructional material is instead presented as diagrams and narration, the cognitive load on the visual channel will be reduced, as it will be only required to process the diagrams. The auditory channel will handle the narration. As a result, neither channel will be overburdened, and more cognitive resources will be available for schema acquisition and automation. Presenting information in two modalities, rather than one, enables the working memory to expand its capacity by simultaneously making use of both available channels. Consequently, students who learn from diagrams and narration tend to perform better on post-tests of problem-solving transfer than students who learn the same material from diagrams and written text.

Evidential Support for the Modality Principle in Instructional Design

The Modality Principle in Non-Interactive Learning Environments

The first experiments that explicitly tested the modality principle were conducted using paper and pencil materials. In a series of six experiments, Mousavi et al. (1995) tested the hypothesis that presenting geometry examples in a mixed modality would produce better learning outcomes than presenting the same examples in a single visual modality. In the second experiment performed by Mousavi et al., students were randomly assigned to three different groups. The first group studied geometry examples from diagrams and written statements (visual-only condition). The second group studied the same material from diagrams and narration (visual-auditory condition), and the third group studied the examples from diagrams, written text and narration that was identical to the written statements (simultaneous condition). The diagrams and written statements were presented to the students on paper, and the narration was played from an audiotape. All students were given 151 seconds to study the first example and 157 seconds to study the second example. Results from post-tests indicated that students in the visual-auditory condition spent significantly less time solving questions similar to the previously studied geometry examples than students who were in the visual-only condition. The other five experiments conducted by Mousavi et al. also provided results supporting the use of the modality principle in instructional design.

In three separate experiments, Tindall-Ford et al. (1997) tested the modality effect with instructional materials that included tables and diagrams varying in their degrees of element interactivity. The materials described electrical engineering concepts and were presented in a paper format to first-year trade apprentices. In the first experiment, diagrams and words with high levels of element interactivity were tested. Students were randomly assigned to either a visual-auditory, visual-only or an integrated group. The visual-only group was presented with diagrams and written text, the visual-auditory group was presented with diagrams and narration, and the integrated group was presented with diagrams and written text that had been integrated into the diagram so as to minimize the learner's visual search. The content of the materials presented to all three groups was identical. After studying the diagrams and words for a fixed period of time, the students were tested on what they had learned. Results showed that students in the audio-visual and integrated groups performed significantly better than students in the visual-only group on tests of practical application and problem-solving transfer. Tindall-Ford et al. explained that the audio-visual group achieved higher results because both auditory and visual channels were used to process incoming information. They also stated that the integrated group's superior performance was a result of working memory needing fewer cognitive resources to mentally integrate the text with the diagrams.

The second experiment by Tindall-Ford et al. (1997) examined the modality effect with table-based visual information, rather than diagrams. In this experiment, only visual-auditory and visual-only groups were involved. The procedure was similar to experiment 1, with a fixed length of time assigned for studying the materials, followed by a testing session. Results again favoured the visual-auditory group, with students in that group reporting lower levels of cognitive load, and achieving higher scores on post-tests.

The third experiment addressed the issue of element interactivity. In the first part of the experiment, students were randomly assigned to either a visual-auditory group, or a visual-only group. The materials included diagrams and text with low element interactivity. These items were considered low in element interactivity because, for the most part, the information units in the diagrams and text could be understood in isolation, without mental integration. Results from post-tests revealed that neither group significantly outperformed the other. These findings are in accordance with the hypothesis from Tindall-Ford et al. (1997). When information is low in element interactivity, it lowers the overall intrinsic cognitive load. With a low intrinsic cognitive load, more resources are available to deal with extraneous and germane cognitive demands. As a result, there is a greater flexibility regarding the instructional design that is employed to convey the material. Even if the information is presented poorly, thus creating a high level of extraneous cognitive load, the intrinsic cognitive load may be sufficiently low enough to keep the overall cognitive load from becoming too high. However, when information is high in element interactivity, the overall intrinsic load is increased. As a result, there is a greater risk of cognitive overload, and extra care must be taken to minimize extraneous cognitive load.

Jeung, Chandler and Sweller (1997) explored the modality effect under conditions of high and low visual search. Under conditions of high visual search, the diagrams were more complex and detailed than the diagrams under conditions of low visual search. Consequently, searching for the necessary visual referents in high visual search environments was a more demanding task than in low visual search environments. Jeung et al. found that students in the auditory-visual condition only performed better than students in the visual-only condition if there were flashing visual cues directing the auditory-visual students' attention towards the appropriate locations on the diagram. However, under conditions of very low visual search, flashing visual cues had no effect on the learning outcomes of the students in the auditory-visual condition.

The above experiments indicate that the modality principle is an effective instructional design technique in certain well-defined conditions. More specifically, the principle has been found beneficial when combining words with diagrams or tables. The modality effect is also only produced in situations that have high levels of element interactivity. In effect, this means that the modality principle should only be applied to words and diagrams that need to be mentally integrated in order to be fully understood. If the words and diagrams can be understood in isolation, the modality principle need not be applied. Jeung et al. (1997) also demonstrated that in conditions of high visual search, narration should be accompanied with visual cues in order to direct the attention of the learner to the appropriate locations on the diagram. Finally, the above experiments tested the modality principle under conditions in which the pace of the presentation was controlled by the system, not the user. This is a common characteristic of most experiments investigating the modality effect. However, as interactive environments become the norm in e-learning, research is being directed towards understanding the effects of the modality principle in more learner-controlled situations. The following section addresses research studies that have investigated the modality principle in interactive learning environments.

The Modality Principle in Interactive Learning Environments

Mayer, Dow and Mayer (2003) examined the effect of the modality principle in an interactive learning environment with an on-screen pedagogical agent. The on-screen pedagogical agent was an animated, lifelike character designed to facilitate the learning process. In the experiment, there were two versions of the interactive environment. In the first version, an on-screen pedagogical agent communicated to students with spoken words. The second version of the program consisted of an on-screen agent communicating to students with on-screen text. Both versions were designed to teach students the functions of an electric motor in an interactive environment. The program displayed a graphic of an electric motor, and students could select any part of the motor to learn more about the individual components. After selecting a component of the motor, students were presented with a series of questions that they could pose to the on-screen pedagogical agent. After the student selected one of the pre-defined questions, the agent would respond. Following the agent's response, students had the option of replaying the answer, or going back to the main menu of questions.

Students had the opportunity to navigate the program for approximately 20 minutes. Once the learning session was complete, they were tested with questions assessing problem-solving transfer. These questions required them to use concepts learned from the program to answer questions such as, "Suppose you switch on an electric motor, but nothing happens. What could have gone wrong?" Results showed that students who learned from the narrated version of the program performed significantly better on tests of problem-solving transfer than students who learned from the on-screen text version of the program. These findings were found promising, as they indicated that the modality principle could be extended beyond system-paced learning environments to more interactive e-learning programs.

Atkinson (2002) similarly examined the modality effect with on-screen pedagogical agents. In this experiment, students were required to study from worked-examples designed to teach proportional reasoning. Students had control over the pace of the instruction, as there was a control panel that enabled students to decide when to go forward or backward a screen. Each worked example was presented visually for the students in all experimental conditions and the modality of presentation differed between groups for only the explanations supplied by the pedagogical agent. Atkinson's experiment consisted of a 2 x 2 factorial design, with the first factor being the physical presence or absence of a pedagogical agent, and the second factor being the modality of presentation of the agent's explanation. After post-tests were administered, Atkinson found that students who had listened to the explanations performed better on tests of near-transfer than students who had read the explanations.

The modality effect demonstrated by Mayer et al. (2003) and Atkinson (2002) differed from the traditional modality experiments in several respects. First, Mayer et al.'s and Atkinson's learning environments gave the users some control over the pace and order of presentation. Second, the experiments examined the modality effect in the context of an environment using on-screen pedagogical agents. Unlike previous experiments (Mousavi et al., 1995; Tindall-Ford et al., 1997), much of the material remained in a visual format for all experimental conditions. Only the modality of the pedagogical agents' explanations was varied between conditions. In the case of Atkinson's study, it seems that the explanations provided by the pedagogical agents may not have been necessary for an expert learner, because the full worked-out examples could be understood without the additional input from the agents.

These two experiments helped to further generalize the modality principle to interactive e-learning environments with pedagogical agents. Further insight regarding the modality effect and learner-control was provided by Tabbers, Martens and van Merriënboer (2004) in an experiment that examined the effect of modality in an interactive environment with no pedagogical agent. In sharp contrast to Atkinson (2002) and Mayer et al. (2003), Tabbers et al. found that students learning from diagrams and written text achieved higher scores on retention and transfer questions than students learning from diagrams and narration. Consequently, this resulted in a reverse modality effect. The retention questions required students to recall concepts from the instructional program, while the transfer questions addressed the students' ability to apply concepts from the instructional program to a new problem-solving situation. The structure of the interactive computer program used in this experiment differed from system-controlled programs by allowing students to move forward and backward between screens at their own pace. In addition, students in the narrated condition had the opportunity to replay the short audio segments on each screen. Tabbers et al. explained that the contradictory findings obtained in the experiments may have been caused by one or more of the following factors:

1. Setting: While most modality experiments have been conducted in a laboratory setting, Tabbers et al. conducted their experiment in a classroom of 40 students.

2. Length of Experiment: The students in Tabbers et al. spent over an hour studying the instructional material. Students in most previous experiments spent only a few minutes learning the material.
3. Content of Instructional Material: Tabbers et al. provided instruction to students on the four component instructional design model. Most previous experiments tested students on mathematics and science related materials.
4. Loading Time of Audio Segments: Students in the audio version of Tabbers et al. had to wait while audio files downloaded, and this delay may have caused a loss of motivation.
5. Pacing of Instruction: Students in Tabbers et al., contrary to students in most other modality experiments, had control over the pace of instruction.

Tabbers et al. argued that the most likely explanation for the reverse modality effect was due to the learner's control over the pace of instruction. They argued that, "with visual texts it is much easier to jump back and forth through the text than with spoken texts that are linear by nature and are much less easy to skim through" (p. 80). Consequently, the learner's control of the pace of instruction could result in visual-only materials producing better learning outcomes than bimodal instructional materials. This is a plausible argument, but it does not explain why there is a discrepancy between the results from Tabbers et al., and those of Atkinson and Mayer et al.

A study that examined the effect of system-pacing and learner-pacing on the modality of instruction was conducted by Tabbers, Martens and van Merriënboer (2001). The experiment consisted of a 2 x 2 factorial design, with one factor being either learner or system control over the pace of instruction, and the second factor being the modality of instruction (visual-only or auditory-visual). Tabbers et al. found that, under the system-pacing condition, students who received instruction in a narrated format scored higher on transfer and retention tests than students who learned from the visual-only instructional materials. However, when students were given control over the pace of instruction, the modality effect disappeared. Tabbers et al. claimed these results demonstrated that the modality effect is not necessarily a result of an increase in working memory resources. Rather, the modality effect occurs because the two senses enable learners to apprehend spoken text and diagrams simultaneously, thus allowing them to make the optimal use of the time available. When diagrams are presented with written text, students must spend time alternating between the diagrams and text. The time spent alternating between the pictorial and textual information will hinder the process of schema acquisition when learning is placed under strict time constraints.

The modality effect has been consistently reproduced under system-paced conditions in a variety of studies (Moreno & Mayer, 1999; Mousavi et al., 1995; Tindall-Ford et al., 1997). However, the evidential support for the modality principle in learner-controlled environments is less convincing. Atkinson (2002) and Mayer et al. (2003) demonstrated the effectiveness of bimodality in interactive environments with on-screen pedagogical agents. In Tabbers et al. (2001, 2004), the modality effect was achieved when pacing was controlled by the computer; but when students were given control of the pace of instruction, the modality effect disappeared in one experiment and was reversed in another. Understanding the extent to which the modality principle can be applied to interactive e-learning environments is crucial for instructional designers. As the World Wide Web becomes an increasingly frequent method for conveying information, it will be necessary to understand how and when to apply the modality principle in an inherently interactive environment. From the experiments explained thus far, it is apparent that a factor such as the pace of instruction may have a significant impact on the effectiveness of the modality principle. Many recently developed e-learning environments differ significantly from the traditional linear, system-paced multimedia programs used in previous modality studies, and it is important to understand how these differences can affect learning in different modalities.

Interactivity in E-Learning Environments

Research has shown that the interactivity found in some e-learning environments can increase a learner's cognitive load due to the significant metacognitive demands incurred when navigating a nonlinear, learner-controlled environment (Shapiro & Niederhauser, 2004). This increase in cognitive load could be detrimental to schema acquisition if the learner's working memory resources are already overburdened by the complexity of the content's element interactivity. However, despite the increase in cognitive load, some studies have reported higher learning outcomes among students given control over the presentation of learning materials (Evans & Gibbons, 2007; Lawless & Brown, 1997). In one study, Mayer and Chandler (2001) examined the effect of allowing students to control the pace of narrated instruction, and they found that those who could exercise control over the pace of instruction performed better on problem-solving transfer tests than students who had no control over the pace of instruction.

Many current e-learning environments enable students control over both the pace and sequence of instruction. As mentioned previously, in order to understand how to create efficient and effective interactive e-learning environments, it is imperative to examine how traditional multimedia instructional design principles can be applied to current e-learning environments. One of the goals of this study is to develop a better understanding of the modality principle in learner-controlled environments by analyzing the effects of modality under conditions that vary in the amount of control afforded to the student. The results will hopefully shed some light on the generality of the modality principle, and also provide empirically-supported suggestions for effectively designing interactive multimedia computer programs.

The Effect of Individual Differences on the Modality Principle

Prior Knowledge and the Modality Principle

It has been well documented that merely adhering to the basic principles of multimedia learning when designing instructional materials is not enough to produce successful learning outcomes. It is also necessary to thoroughly understand what domain-specific knowledge the targeted learners already possess prior to instruction (Kalyuga, 2005).

Prior knowledge can have a significant effect on the learning outcomes of a particular instructional design due to the cognitive differences between novice and expert learners. As mentioned previously, learning occurs when schemas are constructed and integrated into long-term memory. Since schemas are hierarchical networks that enable several pieces of information to be treated as one element in working memory, they help to reduce the cognitive load of the learners who possess them. As described by Kalyuga, Ayres, Chandler and Sweller (2003), expert learners possess well-developed domain-specific schemas to help them to organize and integrate related instructional materials. Novice learners lack these well-developed schemas, and, as a result, they generally need instructional guidance to act as a substitute for the missing schemas. Therefore, when creating instructional materials for novice learners, designers should include sufficient instructional guidance to ensure that the materials support effective learning and minimize cognitive load. However, if the same instructional materials are used to teach learners with a higher level of expertise, these expert learners may find the additional instructional guidance redundant because they already possess the required schemas in their long-term memory. Consequently, instructional guidance that assists novice learners to organize and integrate information may be a source of extraneous cognitive load for expert learners. When the same instructional guidance lowers cognitive load for novice learners and increases cognitive load for expert learners, an expertise reversal effect can occur. As described previously, this effect results from certain instructional techniques losing their effectiveness as learner expertise increases. In extreme cases, an instructional technique can lose its effectiveness to such a degree that it has negative consequences for the expert learner.

The expertise reversal effect has been found in studies examining the split-attention principle, worked-example principle, redundancy principle, as well as in experiments investigating the modality principle. Kalyuga, Chandler and Sweller (2000) tested the interaction of learner expertise and the modality principle when they taught trade apprentices to calculate cutting speed with a two-dimensional graphical device. Initially, the trade apprentices had low levels of domain-specific knowledge, and they were taught with one of four different instructional designs: (a) diagram with written text; (b) diagram with narration; (c) diagram with written text and narration; or (d) diagram-only. In accordance with the modality principle, apprentices in the diagram with narration condition produced significantly higher learning outcomes than apprentices in any of the other treatment groups. However, when the experiment was repeated after the apprentices attended two training sessions, the modality effect disappeared. This experiment demonstrated that when learner expertise increased, the advantage of the modality effect disappeared. While novice learners may benefit from the reduced cognitive load of diagrams and narration, more experienced learners may not experience the same effect. In fact, Kalyuga et al. found that with even more intensive training, trade apprentices studying from the diagram-only began to have a substantial advantage over apprentices studying from the diagram with narration. Thus, the outcome was reversed as prior knowledge increased, resulting in an expertise reversal effect. Kalyuga et al. explained that the expert learners most likely performed more poorly in the dual modality condition because they could not easily ignore or skip the narration, and were therefore required to process what had now become redundant information. Expert learners learning from diagram-only did not have to process the redundant text, and therefore they did not experience the same level of extraneous cognitive load.

Working Memory Capacity, Memory Strategy Skills, and the Modality Principle

Most studies examining individual differences and the modality principle have focused entirely on studying the interaction between learner expertise and modality. However, more recent experiments have begun to investigate other interactions involving individual differences and the modality principle. Seufert, Schütze and Brünken (2008) performed two aptitude-treatment-interaction studies to examine how working memory capacity and memory strategy skills interact with the modality principle. In the first study, Seufert et al. evaluated the participants' memory strategy skills and randomly assigned them to either an audio-visual treatment condition or a visual-only treatment condition. In the audio-visual treatment condition, participants learned a chemistry lesson from a computer program that provided additional help materials in an audio format. In the visual-only treatment condition, participants learned the same chemistry lesson, but in this case the help materials were provided as written text at the bottom of the screen. Seufert et al. found that the modality effect was upheld for learners who were less skilled in memory strategy use, but those with better skills in memory strategy use were equally successful in both conditions.

In the second study, Seufert et al. (2008) examined both memory strategy use and working memory capacity. Similar to the first study, there were two treatment conditions—audio-visual and visual-only. However, unlike the previous experiment, the modality differed between the two treatments for the entire computer program, not just when additional help was provided. Results showed that the modality effect was maintained for learners with low working memory capacity, but the effect was reversed for learners with high working memory capacity. In contrast to the first experiment, there was no interaction found for memory strategy skills.

The results from these aptitude-treatment-interaction studies demonstrate that prior knowledge should not be the only individual difference taken into account when applying multimedia design principles to learning materials. Both working memory capacity and memory strategy skills can impact the effectiveness of the modality principle. However, the discrepancies found in the results between the two studies emphasize the need for further research regarding individual differences and the modality principle. It is imperative that we be able to understand exactly what circumstances contribute to the modality effect.

Context of this Study

The focus of this thesis is the examination of the modality principle in system-controlled and learner-controlled e-learning environments. However, it is important to understand other contextual factors that may have an impact on this study. The students who participated in this experiment were elementary teacher candidates, and the content of the program taught them new methods and concepts in division with fractions. Considering that: (a) a meta-analysis by Hembree (1990) revealed that elementary teacher candidates reported the highest levels of mathematics anxiety of any university students on the Mathematics Anxiety Rating Scale (MARS); and (b) division with fractions has long been known to be a source of confusion and frustration among elementary mathematics teachers (Ma, 1999); it is important to acknowledge and examine what impact mathematics anxiety could have on the learning outcomes of the experiment.

Mathematics Anxiety and the Modality Principle

Mathematics anxiety is defined as “a feeling of tension, apprehension, or fear that interferes with math performance” (Ashcraft, 2002, p. 181). Not surprisingly, highly mathematics-anxious individuals tend to report lower levels of enjoyment, self-confidence and motivation when it comes to doing mathematics (Hembree, 1990). Furthermore, those with mathematics anxiety usually end up taking fewer elective mathematics courses, and they have lower levels of achievement on standardized mathematics tests (Hembree).

Mathematics anxiety and its cognitive consequences. Recent research has examined the possibility that mathematics anxiety may interfere with working memory. Based on Eysenck's theories of anxiety and cognition (see Eysenck & Calvo, 1992), it has been hypothesized that, when attempting to complete a mathematics task, highly mathematics-anxious individuals devote a portion of their limited working memory resources to dealing with the worry and intrusive thoughts brought on by the anxiety reaction. As a result, fewer working memory resources remain available to deal with the task at hand. This puts mathematics-anxious individuals at a severe disadvantage, as they are more likely to experience cognitive overload when attempting to solve mathematics problems that are high in element interactivity. The results from several studies are supportive of this hypothesis (Ashcraft & Faust, 1994; Ashcraft & Kirk, 2001; Faust, Ashcraft & Fleck, 1996). In particular, Ashcraft and Kirk found that highly mathematics-anxious individuals had reduced working memory capacity when performing computation-based working memory span tasks; but there was little correlation between mathematics anxiety and language-based working memory span tasks.

Since the effectiveness of the modality principle is so highly dependent on the cognitive load of the learner, mathematics anxiety could prove to be an influential factor—especially among students learning how to solve mathematics problems that demand significant amounts of working memory resources.

Summary of Literature Review

The modality principle asserts that creating multimedia programs with diagrams and narration will produce better learning outcomes than creating the same programs with diagrams and written text. As explained by Cognitive Load Theory (Paas et al., 2003;

Sweller, 2005) and the Cognitive Theory of Multimedia Learning (Mayer, 2001, 2005), presenting materials in two modalities allows learners to maximize their working memory capacity by making use of both the visual and auditory channels. Although the modality effect has been obtained in numerous studies with various contextual factors, it is still not entirely clear how the effectiveness of the modality principle can be influenced by learner-control. Thus far, preliminary research seems to point to possible nullification, or even a reversal of the modality effect under learner pacing. With further research, we will be able to better identify the conditions required to produce a modality effect in learner-controlled environments.

In addition to learner-control, individual differences can also interact with the modality principle. While most research investigating the interaction between individual differences and multimedia design has focused on the impact of prior knowledge, recent studies have examined such differences as working memory capacity and memory strategy skills. Due to the cognitive consequences experienced by highly mathematics-anxious individuals when attempting to complete mathematics tasks, it is also possible that mathematics anxiety may also prove to interact with modality. However, this link has yet to be thoroughly examined in a research setting.

Purpose of this Study

This thesis examines the implications of the modality principle in both system-controlled and learner-controlled e-learning environments. In my experiment, I investigate the modality principle under conditions that vary in the amount of control afforded to the learner. The study is structured as a 2 x 2 x 2 between-subjects factorial design, with participants learning from a program about division with fractions. The first factor is the modality of presentation (auditory-visual or visual-only). The second factor addresses the control over the pace of presentation, with the pace being controlled by either the learner or the system (learner-paced or system-paced). Finally the third factor considers two options regarding the control over the sequence of instruction. With the first option, the learner has no control over the instructional sequence (system-controlled sequence condition). However, the second option gives learners some control over the sequence of instruction (learner-controlled sequence condition).

Furthermore, considering the context of the experiment (in which elementary teacher candidates are asked to learn new mathematical concepts), this thesis also examines to what extent prior knowledge and mathematics anxiety may influence the learning outcomes of the study.

. In this study, I will examine the following three research questions:

1. To what extent do mathematics anxiety, mental effort, prior knowledge, and engagement predict learning outcomes? What are the relationships among the variables?
2. To what extent does learner-controlled sequencing and pacing have an impact on the effectiveness of the modality principle?
3. To what extent does mathematics anxiety and prior knowledge interact with modality, pacing and sequence-control?

For the first research question, I hypothesize that mathematics anxiety will be negatively correlated with pre-test scores, engagement and post-test scores. Regarding the second research question, I predict that the modality principle will be upheld under system-pacing, and students in the auditory-visual treatment condition will produce higher learning outcomes than students in the visual-only treatment condition. On the other hand, it is expected that the modality effect will disappear when students are provided with control over the pace of instruction.

To answer the third question, I will analyze an aptitude-treatment-interaction with pacing, sequence-control and modality as the treatment factors and mathematics anxiety as the aptitude factor.

Chapter 3: Method

Participants and Design

The participants in this study were students from the eight Elementary Mathematics classes in the Bachelor of Education program at Queen's University. In total, 215 students participated in both the pre-test and instructional component of this study. However, two participants were removed from the final results, as they did not complete the post-test in the allotted time. The last experimental class of the week (n = 27) was also removed from the results due to a combination of very low performance scores on the post-test, and a non-significant correlation between pre-test and post-test scores ($r = .298$; $p = .131$; see Appendix A). The results from this class may have been particularly poor because it was the last class of the afternoon and near the end of the week. With these data removed, a total of 186 participants remained in the study.

There are three sections to this study. The first section describes the demographics of the study population, and also examines the relationships among math anxiety, engagement, mental effort, pre-test scores, and post-test scores. The second section describes a three-factor experimental design examining the effects of modality and learner-control on learning division with fractions. The first factor considers the modality of instruction (visual-only or visual-auditory). The second factor dictates the control over pacing, with either the learner or the computer controlling the pace of instruction (learner-pacing or system-pacing). The third and final factor addresses the learner's control over the sequence of instruction. In the system-controlled sequence condition, participants have no control over the sequence of instruction, while in the learner-controlled sequence condition, learners are allowed to navigate freely within the instructional program. The third section of this study examines how mathematics anxiety and prior knowledge interact with modality, pacing, and sequence-control.

Since previous experiments in multimedia learning have shown that prior knowledge can have an impact on the effectiveness of specific types of multimedia instruction (Moreno & Mayer, 1999), participants were given a pre-test to assess their general knowledge of fractions. After the tests were scored, participants were initially divided into groups of eight. The groups were formed based on pre-test scores, so that participants with similar scores were grouped together. Once these groups were formed, the participants were randomly assigned to the experimental conditions in such a way that allowed each group to have one of its participants in each experimental condition. This procedure, commonly referred to as *stratified random assignment*, increased the validity of the experiment by ensuring that the average level of prior knowledge did not vary significantly from one experimental group to the next.

Participants with very high levels of prior knowledge (i.e., those who scored at least 28 out of a possible 32 points on the pre-test) were removed from the experimental component of the study. As described by Kalyuga et al. (2003), participants with high levels of prior knowledge have well-developed schemas in their long-term memory. Consequently, when processing complicated instructional materials, they are able to treat multiple pieces of information as a single element. As a result, these participants have a lower intrinsic cognitive load than participants who lack well-developed schemas (Schnotz & Kürschner, 2007). Since the total cognitive load is the sum of the intrinsic, extraneous, and germane cognitive load, high prior knowledge participants are less likely to experience cognitive overload from poorly designed instructional materials exhibiting high levels of extraneous cognitive load. Therefore, the high prior-knowledge participants were excluded from this study, as they had less information to learn, and the conditions of the experiment were unlikely to bring about the cognitive overload required to produce a modality effect. Twelve high prior-knowledge learners were removed, leaving 174 participants in the experimental component of the study.

Materials

Pre-test

A paper-and-pencil pre-test was administered to all participants two months before the instructional program. This pre-test was necessary because all participants had some experience solving problems involving division with fractions. Although the instructional program contained material that was new to the participants, their prior knowledge of fraction concepts, and of elementary mathematics in general, varied greatly. Administering a pre-test ensured that all experimental conditions contained similar numbers of high and low prior-knowledge learners.

The pre-test consisted of multiple-choice and open-ended questions, and it addressed both conceptual and procedural knowledge of fractions. The pre-test required participants to: (a) represent fractions with counters, circles, and number lines; (b) compare the size of fractions; (c) perform addition, subtraction, multiplication, and division with fractions; and (d) provide answers to word problems involving fractions. Each question was worth between one and four marks, and each participant's final score was calculated from finding the sum of marks awarded (Cronbach's alpha = 0.77). Participants could achieve a maximum score of 32 marks.

Instructional Program

The 2 x 2 x 2 experimental design required the following eight variations of a computer program: (a) visual-only, system-controlled sequence, system-paced; (b) visual-only, system-controlled sequence, learner-paced; (c) visual-only, learner-controlled sequence, system-paced; (d) visual-only, learner-controlled sequence, learner-paced; (e) auditory-visual, system-controlled sequence, system-paced; (f) auditory-visual, system-controlled sequence, learner-paced; (g) auditory-visual, learner-controlled sequence, system-paced; and (h) auditory-visual, learner-controlled sequence, learner-paced. All programs contained identical content, varying only in their respective methods of presentation. There were five lessons in this program, and the title of each lesson was listed as a menu item on the left-hand side of the computer screen (see Figure 2). Each lesson was composed of three distinct sections. In the first section, participants were presented with a sequence of instructional slides, with each slide containing either a diagram or animation. In visual-only experimental conditions, the slides also contained written explanations; in audio-visual experimental conditions, the slides had oral explanations to accompany the diagrams and animations. The second part of the lesson consisted of a survey question asking participants to rate the amount of mental effort they required to understand the instructional slides. The third part of the lesson presented participants with one or two multiple choice practice questions, based on the material contained in the previous instructional slides. Each multiple-choice question was displayed on a separate screen (see Figure 2). When participants selected and submitted an answer, they were redirected to a new screen indicating whether or not they answered

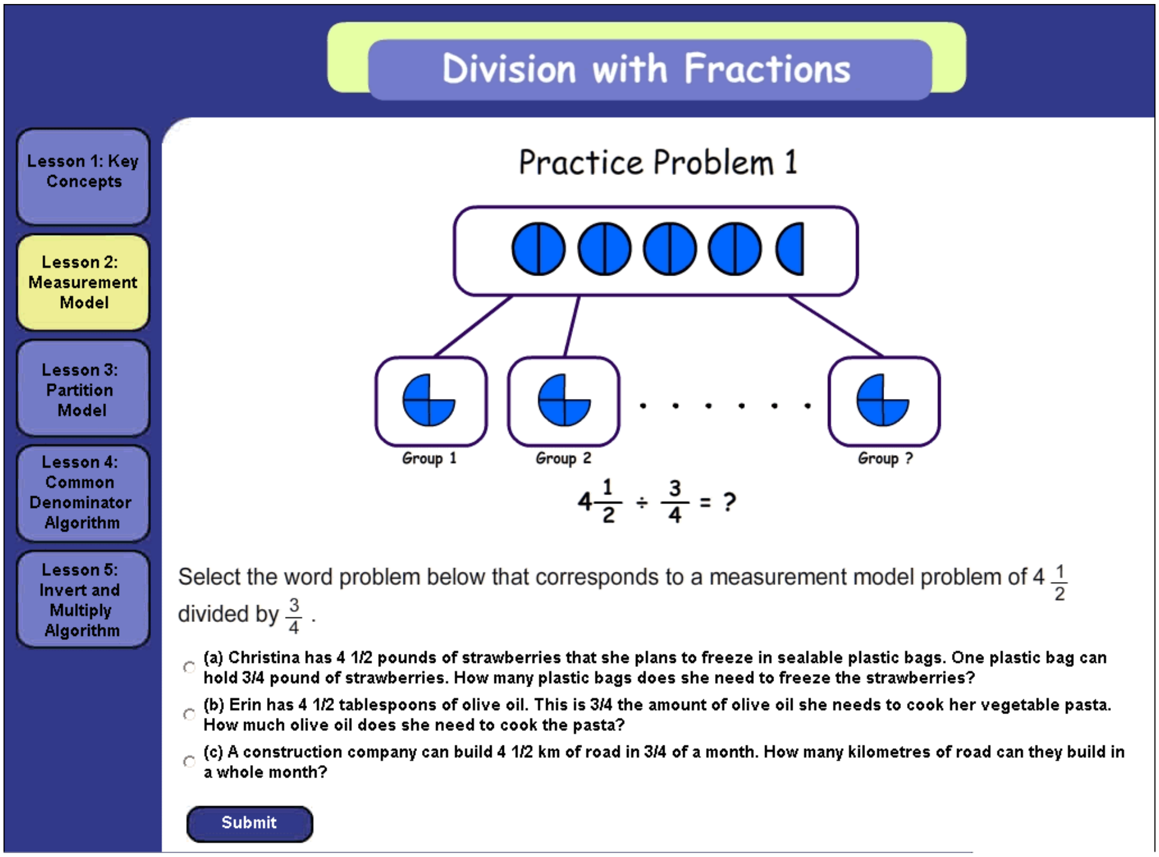

Figure 2. Screenshot of a multiple choice practice question at the end of the Measurement Model lesson.

correctly, and they were presented with an explanation of the correct response (see Figure 3).

The content of the program included a short introductory lesson explaining the partition model and measurement model of division using whole numbers (see Appendix B for a definition of terms). The next four lessons expanded on the introductory lesson, with the second and third lessons explaining the two models of division using fractions rather than whole numbers. The fourth lesson described the common denominator algorithm using the measurement model as a conceptual basis, while the final lesson explained the invert-and-multiply algorithm using the partition model as a conceptual basis. Worked examples were the primary means of explaining the instructional content.

As described previously, this experiment required eight versions of a computer program. Figure 4 is a screenshot of the visual-only, learner-controlled sequence, learner-paced version of the program. In the learner-controlled sequence version of the program, the menu items represented active links to the lessons, and participants were

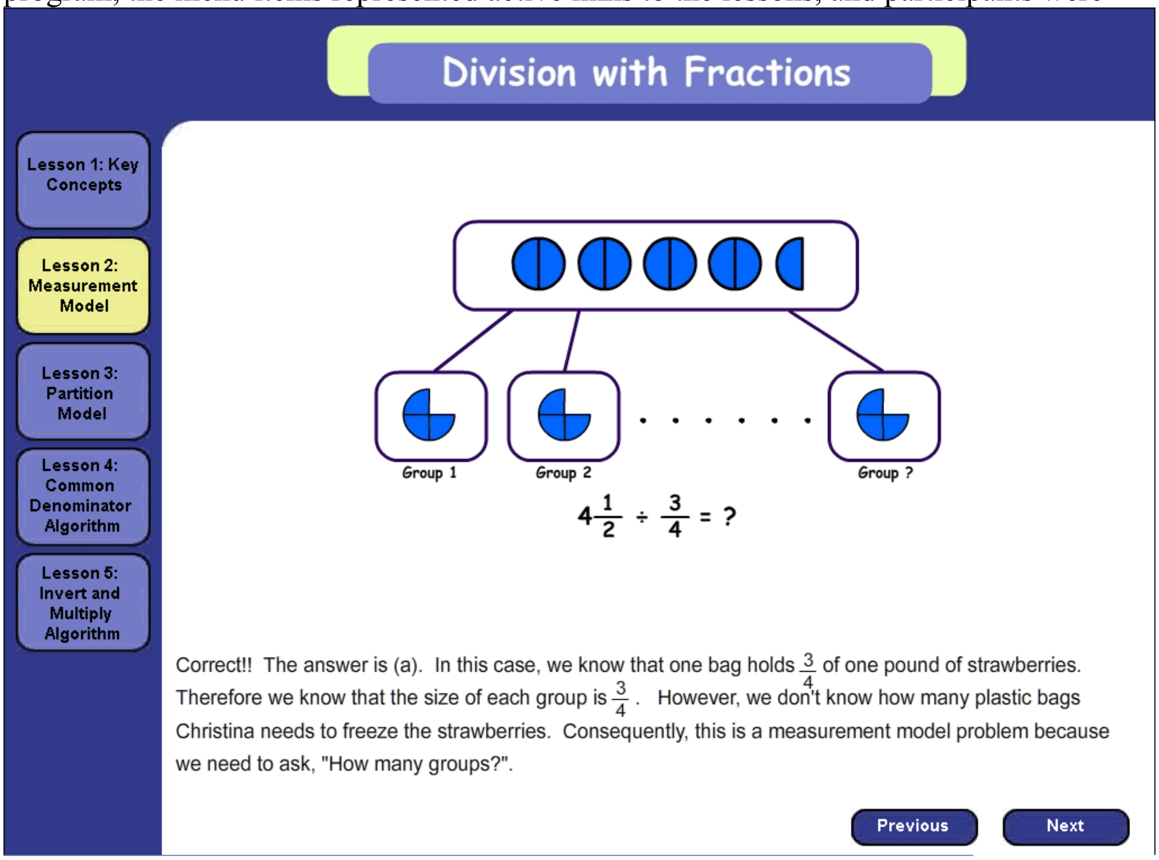

Figure 3. Screenshot of a correct answer page. When students select an answer to a multiple choice question, the next screen informs the learner of the correct answer and an explanation.

able to choose which lessons they wished to study. In the system-controlled sequence version, the program began with the first lesson, and continued through to the last lesson. The lesson titles on the menu were not active links in this version of the program (in order to limit the learner's control over the sequence), but a visual cue would show the participants which of the lessons they were currently studying. In the system-controlled sequence, learner-paced version of the program, each page had a *continue* button, to allow the participants to decide when to proceed to the next screen. However, the learner-controlled sequence, learner-paced version of the program also included a *previous* button in addition to a *next* button, in order to permit participants to navigate

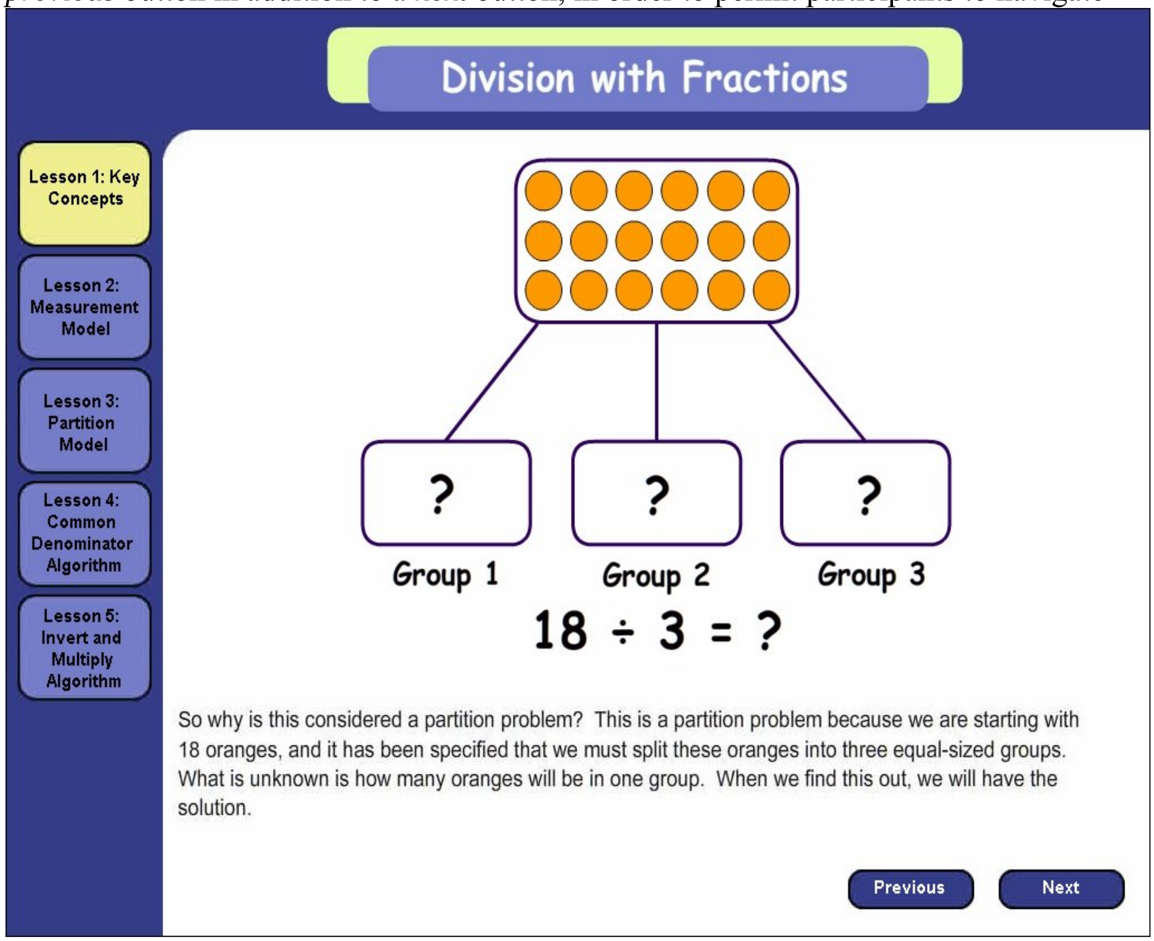

Figure 4. Screenshot of visual-only, learner-controlled sequence, learner-paced program. The *next* and *previous* buttons, combined with active links on the menu, provided the learner with control over the sequence and pace of instruction. Explanations of the diagrams were in a visual-only format as text at the bottom of each screen.

more freely within the learning environment. In the auditory version of the learner-paced program, a *replay* button enabled participants to replay the narration accompanying a particular slide, as demonstrated in Figure 5. In the system-paced program, each slide was presented to the student for a fixed amount of time before proceeding to the next slide. A timer located in the upper right-hand corner of the screen showed participants how much time they had to study each slide. In the visual-only condition of the program, slides consisted of diagrams or animations with accompanying written text. The auditory-visual program included the same diagrams and animations, but the text was presented in an audio format. Additionally, each version of the computer program

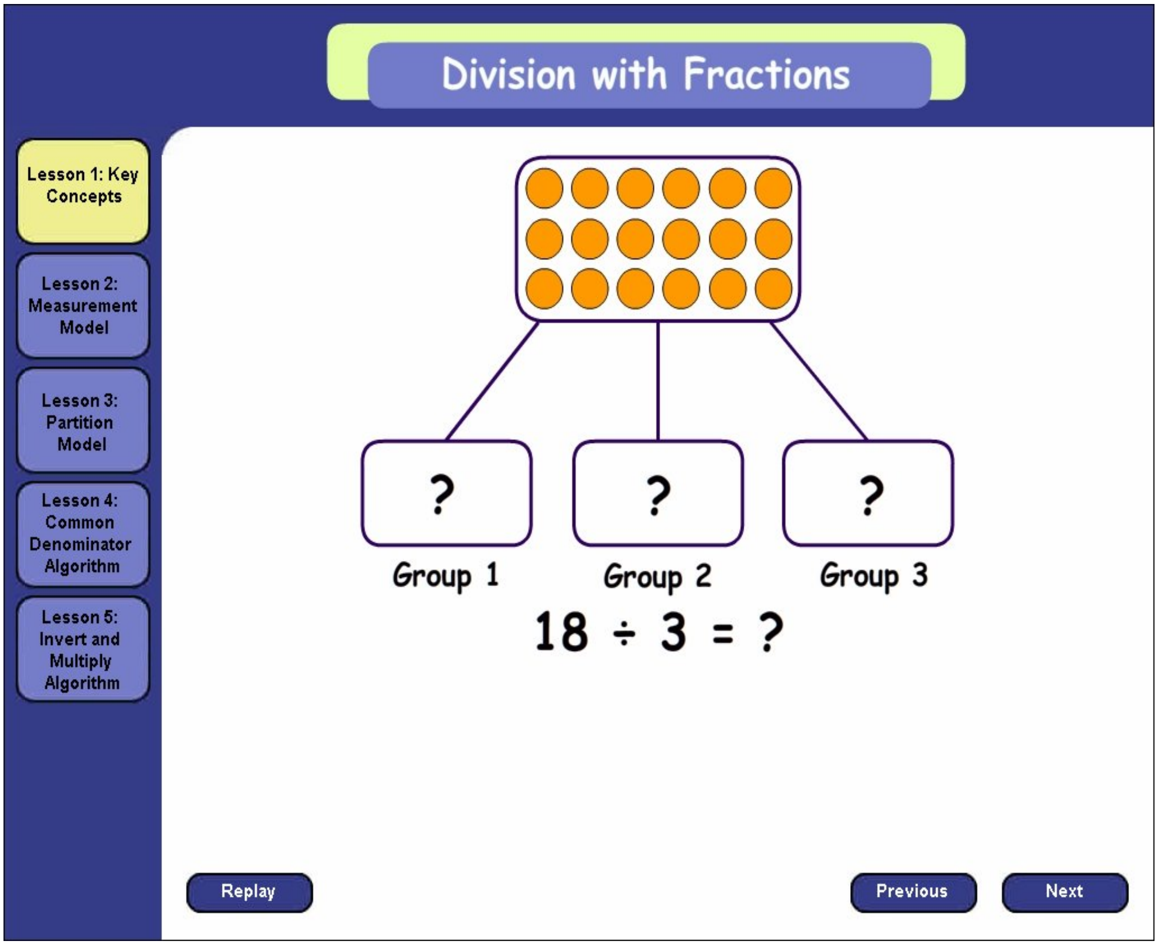

Figure 5. Screenshot of auditory-visual, learner-controlled sequence, learner-paced program. The *next* and *previous* buttons, combined with active links on the menu, provided the learner with control over the sequence and pace of instruction. The *replay* button allowed the learner to listen to the narration multiple times.

recorded to a data file the number of seconds spent on each slide, the viewing sequence of the slides, the responses to the measure of mental effort, and the responses to the multiple choice questions.

Measure of Mental Effort

The subjective measure of mental effort, developed by Paas (1992), consisted of a nine point Likert scale, ranging from *very, very low mental effort* to *very, very high mental effort*. This scale was used to measure the subjective level of mental effort required to understand each of the five lessons. A mean mental effort score was calculated for each participant from their responses to the five mental effort questions (Cronbach's alpha = 0.84).

Basic Concepts Review Sheets

Prior to beginning the instructional program, participants were provided with a set of review sheets describing some of the basic concepts that serve as building blocks for division with fractions (see Appendix C). These concepts included: (a) finding a common denominator; (b) converting improper fractions to mixed fractions and vice versa; and (c) multiplying fractions. The review sheets were intended to refresh participants' memories on concepts and algorithms that they had learned previously, but may have forgotten.

Abbreviated Math Anxiety Scale (AMAS)

The Abbreviated Math Anxiety Scale (see Appendix D), developed by Hopko, Mahadevan, Bare, and Hunt (2003), consisted of nine questions evaluated on a five-point Likert scale from *low anxiety* to *high anxiety*. This questionnaire was completed by the participants after the instructional program, but before they completed the post-test. A mean AMAS score was calculated for each participant to be used for further analysis (Cronbach's alpha = .87).

Demographic Questionnaire

The demographic questionnaire consisted of twelve questions, including a section for comments. Particular attention was paid to the level of engagement during the instructional session, perceived difficulty of the program, and the participants' experience using computers.

Post-test

A paper and pencil post-test with multiple choice and open-ended questions (see Appendix E) was given to participants once they had completed the instructional program. The post-test consisted of 12 questions, with a maximum possible score of 24. The total score was calculated from the sum of the marks awarded for each question correctly answered (Cronbach's alpha = 0.83). The test consisted of retention, near transfer, and far transfer questions, and the participants had as much time as they needed (up until the end of the class period) to finish the post-test. To enhance reliability, the questions in the post-test ranged from very easy to difficult, in order to increase the likelihood of a wide range of scores. Additionally, a second independent rater marked a random sample (n = 23) of the post-tests. The interrater reliability for the 23 post-tests was r = .96 (p<0.001).

Retention and near transfer questions. Seven of the 12 questions on the post-test addressed retention and near transfer (Questions # 1, 2, 3, 4, 6, 11, and 12; see Appendix E). Retention questions determined the participants' ability to recall definitions and algorithms, while near transfer questions examined their ability to solve questions that were structurally identical to the worked examples presented earlier in the computer program. The retention and near transfer score was calculated from the sum of marks awarded to retention and near transfer questions (Cronbach's alpha = 0.68), with a maximum possible score of nine points.

Far transfer questions. The remaining five questions in the post-test were far transfer (Questions # 5, 7, 8, 9, and 10; see Appendix E). The far transfer questions required participants to use their newly acquired knowledge to solve problems in novel situations. The far transfer score was calculated from the sum of marks awarded to the far transfer questions (Cronbach's alpha = 0.78). The maximum possible far transfer score was 15 points.

Procedure

In total, eight classes belonging to the Elementary Mathematics course at Queen's University participated in the experiment. In January, 2008, each participant was given a 20 minute pre-test at the beginning of class, along with a letter of information and consent forms. In April, 2008, students from the eight classes participated in the instructional component of the experiment. The first class was a pilot study of the experiment. This pilot study allowed us to work out the technical issues that arose in setting up a classroom with 40 laptops. With the technical issues resolved from the pilot study, data were collected from the next seven class sessions. The participants began the experiment in a preparation room during their regularly-scheduled class period. In this room, they read over the instructions and review sheets. After approximately 15 minutes, the participants were asked to move to their regular math classroom, which was equipped with 40 laptops. In this room, students were provided with their own laptop and mouse. Participants in the auditory-visual condition were provided with headphones. The classroom had approximately 10 tables, with three to five laptops at each table. After participants took their assigned seats, they were provided with further instructions regarding the procedure of the experiment. Participants began the instructional computer program following the instructions, and they required between 23 minutes and 1 hour 17 minutes to finish the program. When the participants completed the program, they were asked to close the laptop and raise a hand in order to receive the AMAS survey, demographic questionnaire, and post-test. Most participants completed the computer program, surveys, and post-test within one hour and 15 minutes; however, participants who were not able to complete the components of the experiment during the class period were noted by the researcher, and their data was subsequently removed from the analysis.

Data Preparation

Parsing Data Files

A data file was created for each participant when she or he began the instructional computer program. These data files recorded the participants' ratings of mental effort, their answers to practice questions, and the amount of time they spent on each screen. Once the experimental session was complete, all data files were retrieved from the laptops with a USB key. A Java program was used to parse the data files, and calculate the total time each participant spent using the computer program, excluding the time spent answering practice questions and the mental effort questions.

Chapter 4: Results

Participant Data

The data from 186 participants in the Elementary Mathematics course in the Bachelor of Education program at Queen's University were analyzed in this study. One hundred and fifty-one participants were female and 35 were male. The participants' mean age was 25.5 years (SD = 5.0; Min. = 21; Max. = 49), with 74.5% of the participants between the ages of 21 and 25 years. Eighty-seven participants had majored in Arts in their previous undergraduate degree; 56 reported majoring in Social Sciences; nine reported majoring in Physical or Life Sciences; two reported majoring in a Health-Related Field, and one each reported majoring in Mathematics and Communications. The remaining 25 participants reported completing *other* degrees, or multiple majors, before entering the Bachelor of Education program.

Sixty-five participants did not complete any mathematics-related courses during their previous undergraduate degree, and 89 participants completed either one or two mathematics-related courses during their previous degree. Twenty participants completed three or four mathematics-related courses, and the remaining 12 participants completed at least five mathematics-related university-level courses in their previous undergraduate degree.

When asked to indicate how often they use a computer, 184 participants reported using a computer every day. The other two participants reported using a computer two to three times a week. Generally, the participants felt confident about using a computer during the experiment. One hundred and twenty-three participants felt *very confident* using a computer during the study, and 47 participants felt *confident*. Fourteen participants were *somewhat confident* using a computer, one participant felt *not very confident* and one more participant felt *not confident at all* using a computer during the experiment.

Descriptive Statistics

Abbreviated Math Anxiety Scale (AMAS)

Table 1 shows the means and standard deviations for the nine items on the AMAS questionnaire. The range of scores for the individual survey items varied greatly. *Taking an examination in a math course* was reported to produce the highest levels of anxiety, while participants also described *having to use tables in the back of a math book* as causing relatively low levels of anxiety.

Table 1

Descriptive Statistics for Nine Items on AMAS (1 – Low Anxiety to 5 – High Anxiety)

Survey Item	Mean	SD
Having to use the tables in the back of a math book.	1.83	1.01
Thinking about an upcoming math test 1 day before.	3.51	1.10
Watching a teacher work an algebraic equation on the blackboard.	2.54	1.27
Taking an examination in a math course.	4.23	1.06
Being given a homework assignment of many difficult problems that is due the next class meeting.	3.71	1.13
Listening to a lecture in a math class.	2.19	1.20
Listening to another student explain a math formula.	2.18	1.15
Being given a "pop" quiz in a math class.	3.97	1.15
Starting a new chapter in a math book.	1.94	1.02

Four participants had missing or unclear responses to one or more items on the AMAS questionnaire. For each participant with missing or unclear data, a mean AMAS score was calculated from their responses to the remaining AMAS variables. This mean AMAS score was used to replace the missing values.

Pre-test

The mean final score for the pre-test was 19.67 out of a possible 32 marks, with a standard deviation of 4.93. Figure 6 shows the distribution of the pre-test scores for the 186 participants.

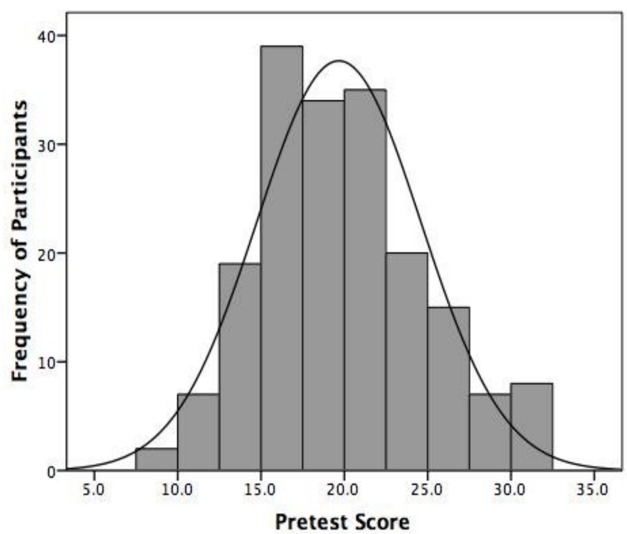

Figure 6. Distribution of pre-test scores (n = 186), with normal curve.

Engagement

Upon completing the instructional program, participants were asked in the demographic questionnaire to rate the amount of effort they put into the study using a five-point Likert scale. Table 2 shows the distribution of the responses.

Table 2

Distribution of Participants' Responses Rating their Level of Engagement

Level of Engagement	Frequency	Percent
Not engaged at all	4	2.2
Not very engaged	24	12.9
Somewhat engaged	41	22.0
Fairly engaged	82	44.1
Very engaged	35	18.8

Perceived Difficulty of Instructional Program

Once the instructional program was completed, participants also used a five-point Likert scale in the demographic questionnaire to report their perceived difficulty of learning the division with fractions computer program. Table 3 shows the distribution of responses for this survey question.

Table 3

Distribution of Participants' Responses Reporting their Perceived Difficulty of Learning the Division with Fractions Computer Program.

Level of Difficulty	Frequency	Percent
Easy	23	12.4
Fairly Easy	63	33.9
Neither easy nor difficult	47	25.3
Fairly Difficult	42	22.6
Difficult	11	5.9

Measure of Mental Effort

Table 4 shows the mean mental effort score reported by participants at the end of each lesson. Due to technical problems with a few of the computers, the mental effort scores of eight participants were lost. Eight other participants selected the multiple choice option *I choose not to answer this question* on at least one occasion. Consequently, these 16 participants were excluded when calculating the mean mental effort scores. Six other participants responded to some mental effort questions, but not all. In this case, the missing data were replaced with the mean mental effort score from all remaining participants for the particular lesson.

Table 4

Mean Mental Effort Scores (1 = very, very low mental effort; 9 = very, very high mental effort) for Participants at the End of Each Lesson

Lesson Number	*n*	Mean	Standard Deviation
Lesson 1: Key Concepts	165	3.85	1.45
Lesson 2: Measurement Model	166	5.33	1.49
Lesson 3: Partition Model	167	6.31	1.46
Lesson 4: Common Denominator Algorithm	169	4.67	1.62
Lesson 5: Invert-and-Multiply Algorithm	170	5.42	1.84

Learning Time

The number of seconds spent viewing each screen was recorded to a data file for each participant. As the mental effort scores were recorded to the same data files as the learning time, the learning time data were also lost for eight participants. The mean total learning time, including the time spent answering practice problems and mental effort survey questions at the end of each lesson, was 44.5 minutes (SD = 8.9 minutes). The mean learning time, excluding the time spent on both the practice problems and mental effort survey questions, was 33.6 minutes (SD = 6.5 minutes).

Post-test Scores

Table 5 shows the mean, standard deviation, skewness, and kurtosis for the post-test scores.

Table 5

Descriptive Statistics for Post-test Scores

Post-test Score	Mean	SD	Skewness (SE)	Kurtosis (SE)
Total score (max. score = 24)	11.63	5.53	.208 (.178)	-.637 (.355)
Retention and near transfer score (max. score = 9)	5.88	2.06	-.578 (.178)	.011 (.355)
Far transfer score (max. score = 15)	5.75	4.03	.503 (.178)	-.788 (.355)

The retention and near transfer score formed a negatively-skewed distribution, as many participants achieved near perfect scores. However, the far transfer score produced a more positively-skewed distribution, as the participants found these questions considerably more difficult to answer.

Relationships Between Mathematics Anxiety, Mental Effort, Engagement, Pre-test and Post-test Total Score

Table 6 shows the correlations between the mean AMAS, the mean measure of mental effort, level of engagement, pre-test and post-test total score.

Table 6

Correlations between Mathematics Anxiety, Mental Effort, Engagement, Pre-test, and Post-test Total Score

Variable	1	2	3	4	5
1. Mean AMAS	—	.524**	-.291**	-.512**	-.429**
2. Mean Measure of Mental Effort		—	-.029	-.424**	-.342**
3. Level of Engagement			—	.264**	.455**
4. Pre-test				—	.555**
5. Post-test Total Score					—

**p< .01 (2-tailed).

With the exception of the relationship between mental effort and engagement, all correlations were significant ($p < .01$). As expected, there was a strong positive correlation between pre-test and post-test total scores. Additionally, the participants' reported engagement with the instructional program had a significant positive correlation with the post-test scores, revealing that as engagement increased, post-test total scores tended to increase as well. Mathematics anxiety and the participants' reported mental effort required to understand the program both had significant negative correlations with the post-test scores.

A multiple regression analysis was performed to examine how level of engagement, pre-test, mean AMAS and mean measure of mental effort could predict the post-test total score. Using the simultaneous entry method, a significant model emerged, $F(4, 165) = 31.13$, $p < 0.001$). Table 7 shows a summary of the analysis.

Table 7

Simultaneous Entry Multiple Regression Analysis with Post-test Total Score as the Response Variable (n = 170)

Predictor Variable	*B*	*SE B*	β	*p*-value
Mean AMAS	-.591	.526	-.085	.263
Mean Measure of Mental Effort	-.546	.316	-.123	.086
Level of Engagement	1.786	.347	.318	<.001
Pre-test	.451	.082	.388	<.001

Note. $R^2 = .430$.

In this model, level of engagement and pre-test scores are both significant predictors of the post-test total score. The four predictors account for .43 of the variance of the post-test total score.

Examination of Treatment Effects and Interactions

Study Sample

One hundred and seventy-four participants were included in this section of the analysis. The descriptive statistics for this sample are in Appendix F.

Three-Factor Analysis of Variance

The post-test total score, retention and near transfer score, far transfer score, mean mental effort score, engagement score and perceived difficulty of program score were all analyzed individually with a three-factor between-subjects ANOVA. The three factors were: (a) modality (audio-visual (AV) or visual-only (VO)); (b) pacing (learner-pacing (LP) or system-pacing (SP)); and (c) control of sequence (learner-controlled sequence (LS) or system-controlled sequence (SS)). A significance level of $p < .05$ was applied to all statistical tests, unless otherwise stated.

Total post-test score. The three-factor ANOVA showed a significant interaction of pacing and modality $F(1,166) = 4.87$, $p = .029$, $\eta_p^2 = 0.028$ (see Appendix G for the full ANOVA results).

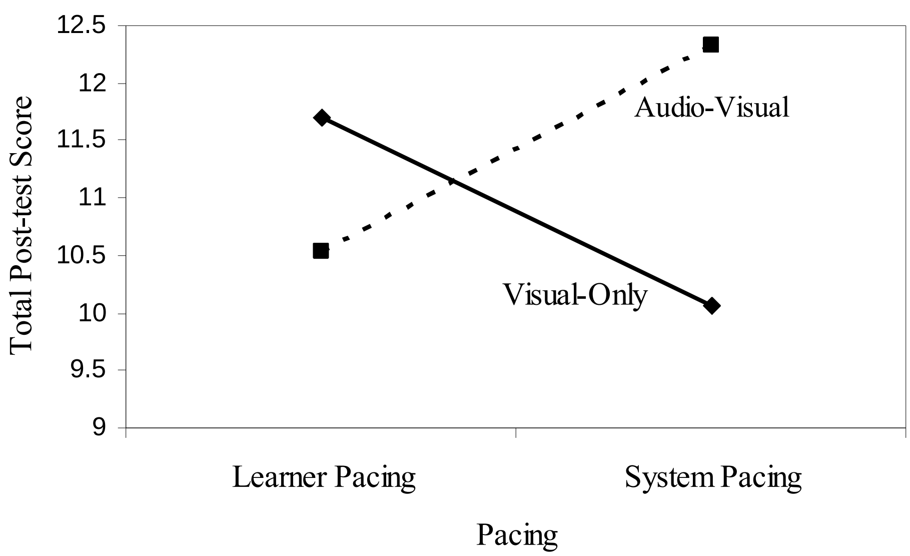

Figure 7. Interaction plot of pacing and modality on the total post-test score.

Figure 7 shows that under system-pacing the modality effect was obtained, as participants in the audio-visual condition tended to achieve higher total post-test scores (M = 12.33;

SD = 5.79) than those in the visual-only condition (M = 10.06; SD = 5.08). However, under learner-pacing, the effect was reversed, as participants in the visual-only condition tended to achieve the higher total post-test scores (M = 11.70; SD = 5.15) when compared to those in the audio-visual condition (M = 10.53; SD = 4.93). A simple main effects analysis using a Bonferroni adjustment for multiple comparisons revealed that the effect of modality was significant only under the system-pacing condition $F(1, 166) = 4.22$, $p = .041$, $\eta_p^2 = 0.025$. Under learner-pacing, there was no significant effect of modality $F(1, 166) = 1.16$, $p = .282$ (ns), $\eta_p^2 = 0.007$.

Retention and near transfer score. A three-factor ANOVA with the retention and near transfer score as the outcome variable revealed no significant main effects or interactions (see Appendix H for the full ANOVA results).

Far transfer score. As with the post-test total score, there was a significant interaction of pacing and modality $F(1,166) = 5.49$, $p = .02$, $\eta_p^2 = 0.032$ (see Appendix I for full ANOVA results). The interaction plot in Figure 8 shows that under the system-pacing condition, the modality effect was achieved, as participants learning from the audio-visual version of the program tended to perform better on far transfer questions (M = 6.40; SD = 4.33) than participants learning from the visual-only version of the program (M = 4.65; SD = 3.26). This situation was reversed in the learner-pacing condition, as participants in the visual-only treatment condition tended to have higher far transfer scores (M = 5.66; SD = 3.72) than participants in the audio-visual treatment condition (M = 4.81; SD = 3.58). A simple main effects analysis using a Bonferroni adjustment for multiple comparisons revealed that the effect of modality was significant only under the system-pacing condition $F(1, 166) = 4.86$, p = .029, $\eta_p^2 = 0.028$. Under learner-pacing, there was no significant effect of modality $F(1, 166) = 1.26$, p = .262 (ns), $\eta_p^2 = 0.008$.

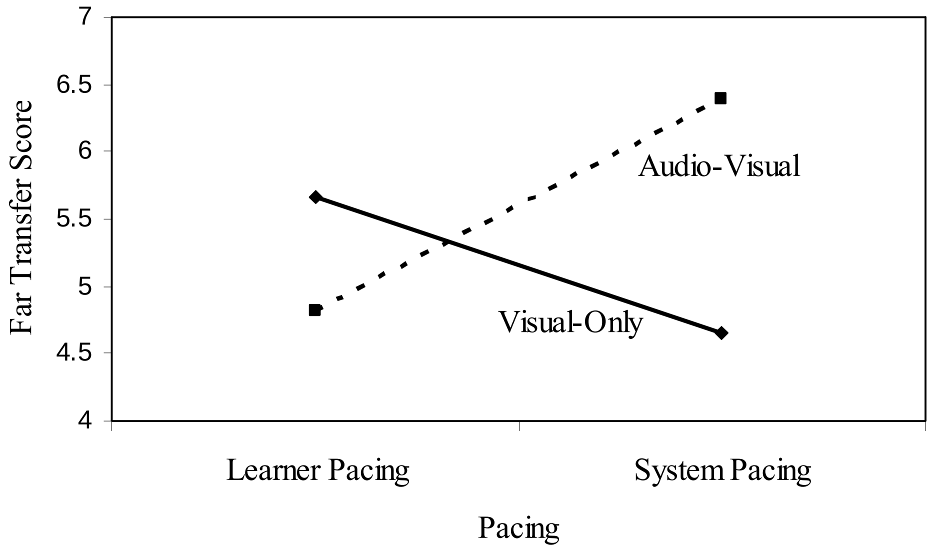

Figure 8. Interaction plot for modality and pacing with far transfer score as the outcome variable.

Mean mental effort score. Another three-factor ANOVA, with the mean mental effort score as the outcome variable, revealed a main effect of modality $F(1,153) = 5.22$, p = .024, $\eta_p^2 = 0.033$ (see Appendix J for full ANOVA results). Participants in the visual-only treatment condition reported significantly higher mental effort scores (M = 5.40; SD = 1.26) than participants in the audio-visual condition (M = 4.98; SD = 1.18).

Engagement score. A three-factor ANOVA with engagement score as the outcome variable revealed no significant main effects or interactions (see Appendix K for the full ANOVA results).

Perceived difficulty of program score. A three-factor ANOVA with perceived difficulty of program score as the outcome variable revealed no significant main effects or interactions (see Appendix L for the full ANOVA results).

Learning Time For Each Treatment Condition

The mean learning times and standard deviations for all treatment conditions were calculated (see Table 8). This descriptive analysis was performed to determine whether superior performance outcomes in different treatment conditions could possibly be attributed to increased time spent learning the instructional computer program. To further examine the relationship between learning time and post-test score, a Pearson product-moment correlation coefficient was calculated for the two variables ($r = 0.063$; $p = .414$), and no significant correlation was found.

Table 8

Mean Amount of Time Each Treatment Condition Spent Learning from Instructional Computer Program

Sequence-Control	Modality	
	Visual-Only	Audio-Visual
	Learner Pacing	
Learner-Controlled	1605.8 (SD = 498.8)	2297.1 (SD = 296.8)
System-Controlled	1707.8 (SD = 391.8)	2118.0 (SD = 486.0)
	System-Pacing	
Learner-Controlled	2145.4 (SD = 167.7)	2100.7 (SD = 218.9)
System-Controlled	2092.0 (SD = 127.4)	2082.2 (SD = 110.2)

Note. Time recorded in seconds.

The results from Table 8 show general patterns. First of all, it seems that participants in the learner-pacing, visual-only conditions generally spent less time learning from the instructional computer program than participants in the other treatment conditions. Secondly, the standard deviations obtained from the learner-pacing treatment conditions were generally much larger than the standard deviations obtained from the system-pacing conditions. This is not surprising, as participants in the learner-pacing conditions had control over the time spent learning the program, whereas participants in the system-pacing conditions were provided with relatively fixed amounts of time to learn the instructional computer program.

Aptitude-Treatment-Interactions (ATI)

Interaction of Mathematics Anxiety with Modality, Pacing, and Sequence-Control

To examine how mathematics anxiety interacts with modality, pacing, and sequence-control, two aptitude-treatment-interaction analyses were performed with mathematics anxiety (i.e., AMAS score) as the aptitude factor, and modality, pacing, and sequence-control as the treatment factors. The following predictors were entered simultaneously into each regression analysis: AMAS score, sequence-control, pacing, modality, sequence-control x modality, pacing x modality, sequence-control x pacing, sequence-control x pacing x modality, AMAS score x modality, AMAS score x pacing, AMAS score x sequence-control, AMAS score x sequence-control x pacing, AMAS score x pacing x modality, AMAS score x sequence-control x modality, and AMAS score x pacing x modality x sequence-control. Effect coding was applied to the categorical variables (learner-pacing = 1; system-pacing = -1; learner-controlled sequencing = 1; system-controlled sequencing = -1; visual-only = 1; audio-visual = -1). The values for the interaction terms were obtained by calculating the products of the appropriate coded variables and raw mean AMAS scores. In the first regression analysis, the dependent variable was retention and near transfer score. The second regression analysis used far transfer score as the dependent variable.

ATI with retention and near transfer score. The regression model was significant with retention and near transfer score as the dependent variable, $R^2 = .166$, $F(15, 173) = 2.09$, p = .013. However, with the exception of mathematics anxiety ($\beta = -.360$; $t(173) = -4.491$; $p<0.001$), there were no significant main effects or interactions.

ATI with far transfer score. A significant model also emerged in the analysis with far transfer score as the dependent variable, $R^2 = .221$, $F(15, 173) = 2.98$, p < .001 (see Appendix M for full regression results). In addition to finding significant main effects of AMAS score ($\beta = -.318$; $t(173) = -4.10$; $p<0.001$), and sequence-control ($\beta = -.921$; $t(173) = -2.93$; $p = 0.004$), and a significant interaction of modality and pacing ($\beta = .857$; $t(173) = 2.73$; $p = 0.007$), two significant interactions involving mathematics anxiety and the format of instruction were found.

First, a significant interaction was found for AMAS score x modality x pacing ($\beta = -.703$; $t(173) = -2.25$; $p = 0.026$). To aid the interpretation of the interaction, a simple slopes approach was taken (see Aiken & West, 1991). When simple slopes are graphed, they show the regression of the dependent variable on an independent variable at certain pre-selected levels of the continuous variable, for instance at +1 and -1 standard deviations. Figure 9 shows a simple slopes plot of the interaction, with low anxiety and high anxiety indicating values one standard deviation below and above the mean AMAS score, respectively. Figure 9 demonstrates that there was evidence of a modality effect for low mathematics-anxious participants in the system-pacing condition. Low mathematics-anxious participants learning from narration and diagrams tended to achieve higher far transfer scores than low mathematics-anxious participants learning from written text and diagrams. However, the effect seemed to reverse for the low mathematics-anxious participants in the learner-paced conditions. Regarding the highly mathematics-anxious participants, there was no evidence to suggest a modality effect, or reverse modality effect, in either pacing condition. In all four conditions, highly mathematics-anxious participants achieved rather low far transfer scores.

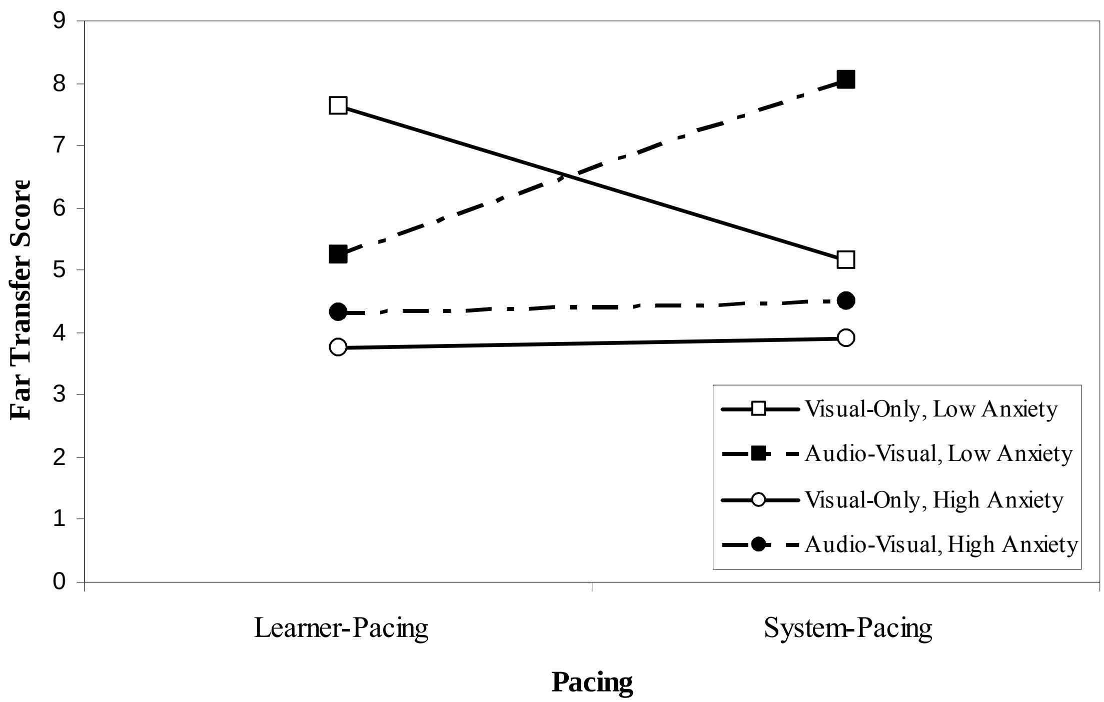

Figure 9. Simple slopes plot of the interaction between modality, pacing and anxiety. Low anxiety and high anxiety indicate values one standard deviation below and above the mean AMAS score.

The second significant interaction between mathematics anxiety and format of instruction was AMAS score x sequence-control ($\beta = .867$; $t(173) = 2.77$; $p = 0.006$). Figure 10 shows that low mathematics-anxious participants tended to perform best under system-controlled sequence conditions. Under learner-controlled sequencing, the low mathematics-anxious participants tended to achieve scores only marginally higher than highly mathematics-anxious participants. The highly mathematics-anxious participants performed poorly in both conditions, although they tended to obtain marginally higher scores in the learner-controlled sequence condition.

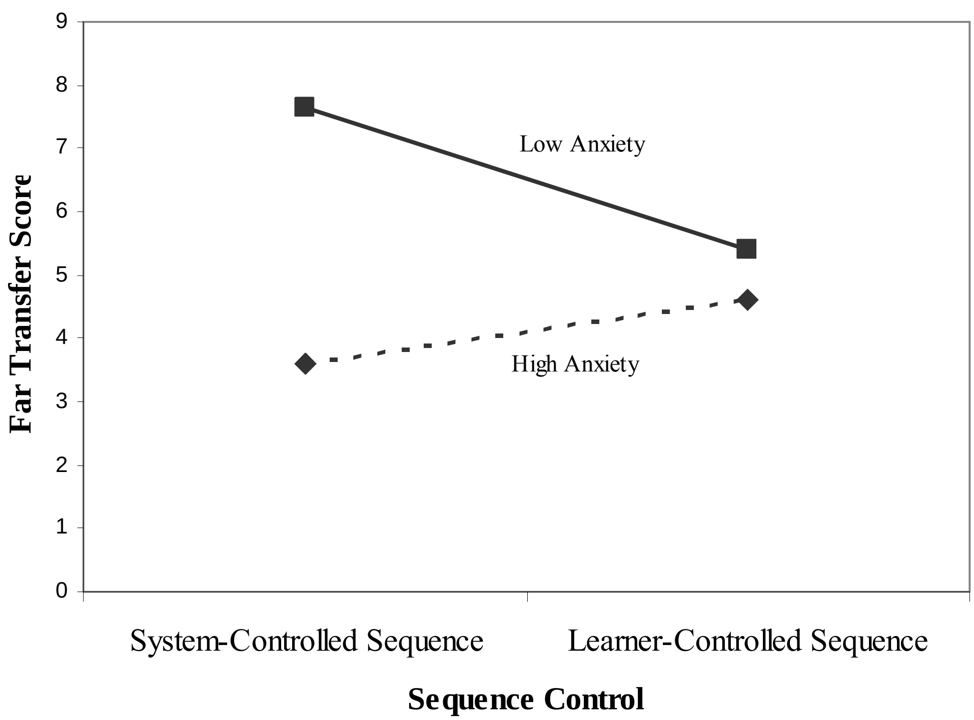

Figure 10. Simple slopes plot of the interaction between sequence-control and mathematics anxiety. Low anxiety and high anxiety indicate values one standard deviation below and above the mean AMAS score.

Interaction of Prior Knowledge with Modality, Pacing, and Sequence-Control

The same method used to examine the interaction between mathematics anxiety and format of instruction was also applied to investigate the interaction of prior knowledge with modality, pacing, and sequence-control. Two analyses were performed with prior knowledge (i.e., pre-test score) as the aptitude factor, and modality, pacing, and sequence-control as the treatment factors. The following predictors were entered simultaneously into each regression analysis: pre-test score, sequence-control, pacing, modality, sequence-control x modality, pacing x modality, sequence-control x pacing, sequence-control x pacing x modality, pre-test score x modality, pre-test score x pacing, pre-test score x sequence-control, pre-test score x sequence-control x pacing, pre-test score x pacing x modality, pre-test score x sequence-control x modality, and pre-test score x pacing x modality x sequence-control. Effect coding was applied to the categorical variables (learner-pacing = 1; system-pacing = -1; learner-controlled sequencing = 1; system-controlled sequencing = -1; visual-only = 1; audio-visual = -1). The values for the interaction terms were obtained by multiplying the coded variables with the raw total pre-test scores, when appropriate. As was the case when examining the mathematics anxiety and format of instruction interaction, the dependent variable in the first regression analysis was the retention and near transfer score. The second regression analysis used the far transfer score as the dependent variable.

ATI with retention and near transfer score. The regression model was significant with retention and near transfer score as the dependent variable, $R^2 = .192$, $F(15, 173) = 2.50$, p = .002. However, with the exception of prior knowledge ($\beta = .389$; $t(173) = 5.286$; $p<0.001$), there were no significant other main effects or interactions.

ATI with far transfer score. The regression model was also significant in the analysis with far transfer score as the dependent variable, $R^2 = .333$, $F(15, 173) = 5.25$, p < .001 (see Appendix N for full regression results). In addition to finding significant main effects of pre-test score ($\beta = .499$; $t(173) = -7.46$; $p<0.001$), and sequence-control ($\beta = .688$; $t(173) = 2.18$; $p = 0.031$), and a significant interaction of modality, sequence-control, and pacing ($\beta = .898$; $t(173) = 2.95$; $p = 0.004$), three significant interactions involving prior knowledge and the format of instruction were found.

First, a significant interaction was found for pre-test score x modality x pacing ($\beta = .745$; $t(173) = 2.42$; $p = 0.017$). Figure 11 is a simple slopes plot of the interaction, with *high prior knowledge* and *low prior knowledge* representing values one standard deviation above and below the mean pre-test score. The figure shows that there was evidence of a modality effect for high prior-knowledge participants in the system-pacing condition, because high prior knowledge participants in the audio-visual condition tended to achieve higher far transfer scores than high prior knowledge participants in the visual-only condition. The effect seemed to reverse for the high prior knowledge participants in the learner-paced conditions. Figure 11 also demonstrates that low prior knowledge participants tended to perform poorly in all four conditions. Consequently, there was no evidence of a modality effect, or reverse modality effect, for low prior knowledge participants.

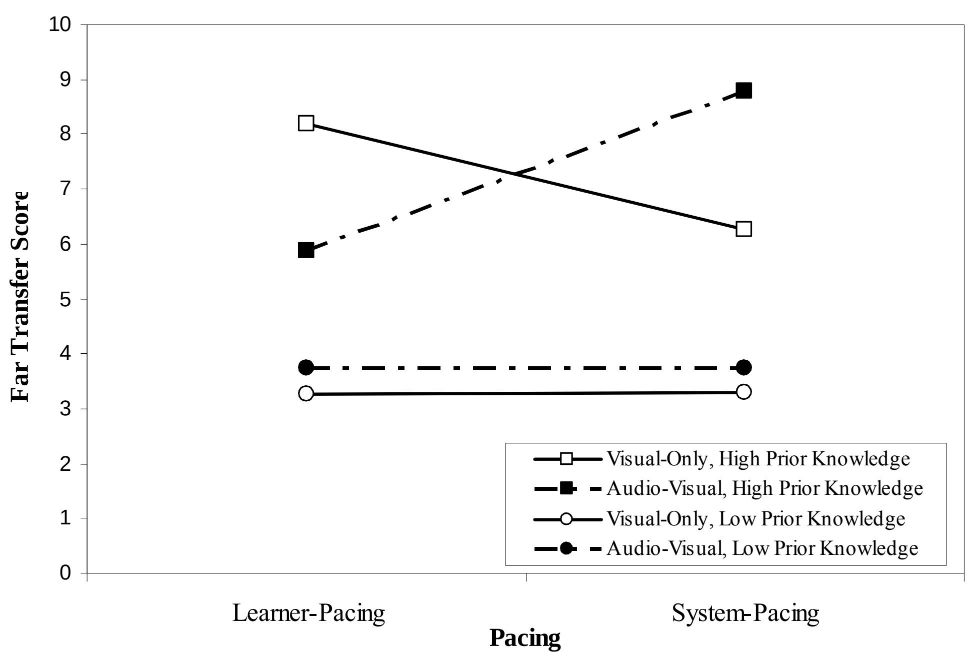

Figure 11. Simple slopes plot of the interaction between modality, pacing and prior knowledge. High prior knowledge and low prior knowledge indicate values one standard deviation above and below the mean pre-test score.

A second significant interaction was found for pre-test score x sequence-control (β = -.753; $t(173)$ = -2.45; p = 0.015). The simple slopes plot depicted in Figure 12 shows that high prior knowledge participants tended to perform best under system-controlled sequence conditions, and low prior knowledge participants performed poorly in both conditions.

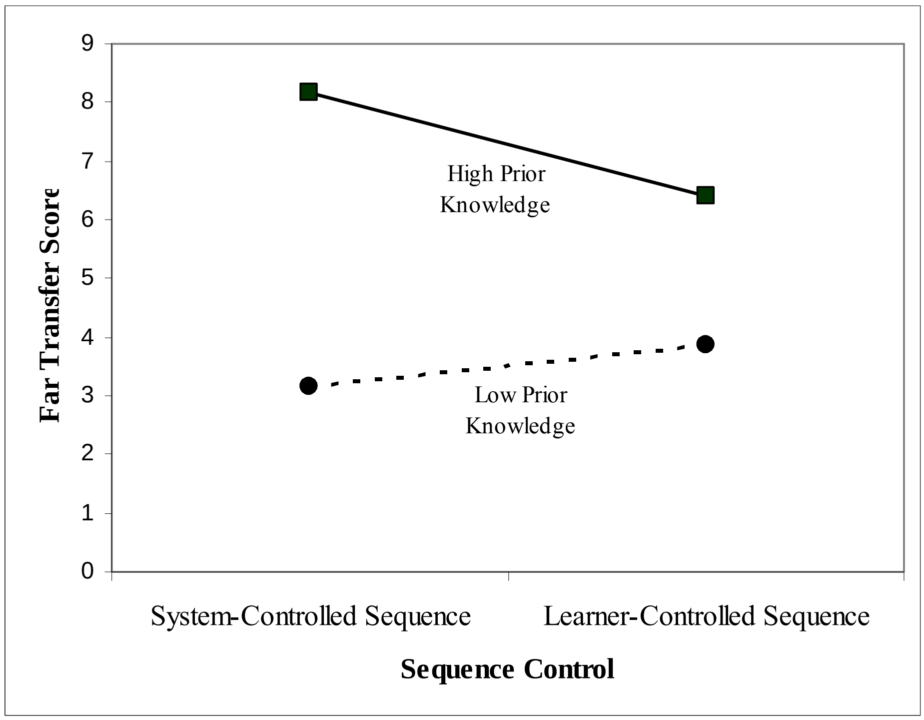

Figure 12. Simple slopes plot of the interaction between sequence-control and prior knowledge. High prior knowledge and low prior knowledge indicate values one standard deviation above and below the mean pre-test score.

The third significant interaction involving prior knowledge was observed for prior knowledge x modality x pacing x sequence-control (β = -.885; $t(173)$ = -2.90; p = 0.004). Figure 13 depicts a simple slopes plot of the interaction. The figure demonstrates that high prior knowledge participants in all conditions tended to achieve better far transfer scores than the low prior knowledge participants. For high prior knowledge participants, there seemed to be a modality effect under system-pacing conditions, as those in the audio-visual condition tended to achieve higher far transfer scores than those in the visual-only condition. Another type of interaction was observed for low prior knowledge participants, although it is not clear if the differences were significant. The low prior knowledge participants tended to perform more poorly in the audio-visual conditions when they had either complete control (learner-controlled sequencing and learner-pacing) or no control (system-controlled sequencing and system-pacing) over the instructional materials. On the other hand, low prior knowledge learners tended to perform better in the audio-visual conditions when they had limited control over the instructional materials (learner-controlled sequencing and system-pacing, or system-controlled sequencing and learner-pacing).

To assist in the interpretation of the four-way interaction, a simple effects approach was taken, examining the interaction of modality, pacing, and prior knowledge under (a) learner-controlled sequencing and (b) system-controlled sequencing. Within each, the following predictor variables were entered simultaneously into regression analysis: pre-test score, modality, pacing, pre-test score x modality, pre-test score x pacing, modality x pacing, and pre-test score x modality x pacing. In the learner-controlled sequence condition, the model was significant, $R^2 = .201$, $F(7, 82) = 2.94$, $p = .008$. However, there were no significant interactions and only a significant main effect of pre-test score ($\beta = .363$; $t(82) = 3.592$; $p = .001$).

When the predictor variables were entered simultaneously into a regression analysis under the system-controlled sequence condition, a significant model also emerged $R^2 = .445$, $F(7, 76) = 8.72$, $p < .001$. In addition to a pre-test score main effect

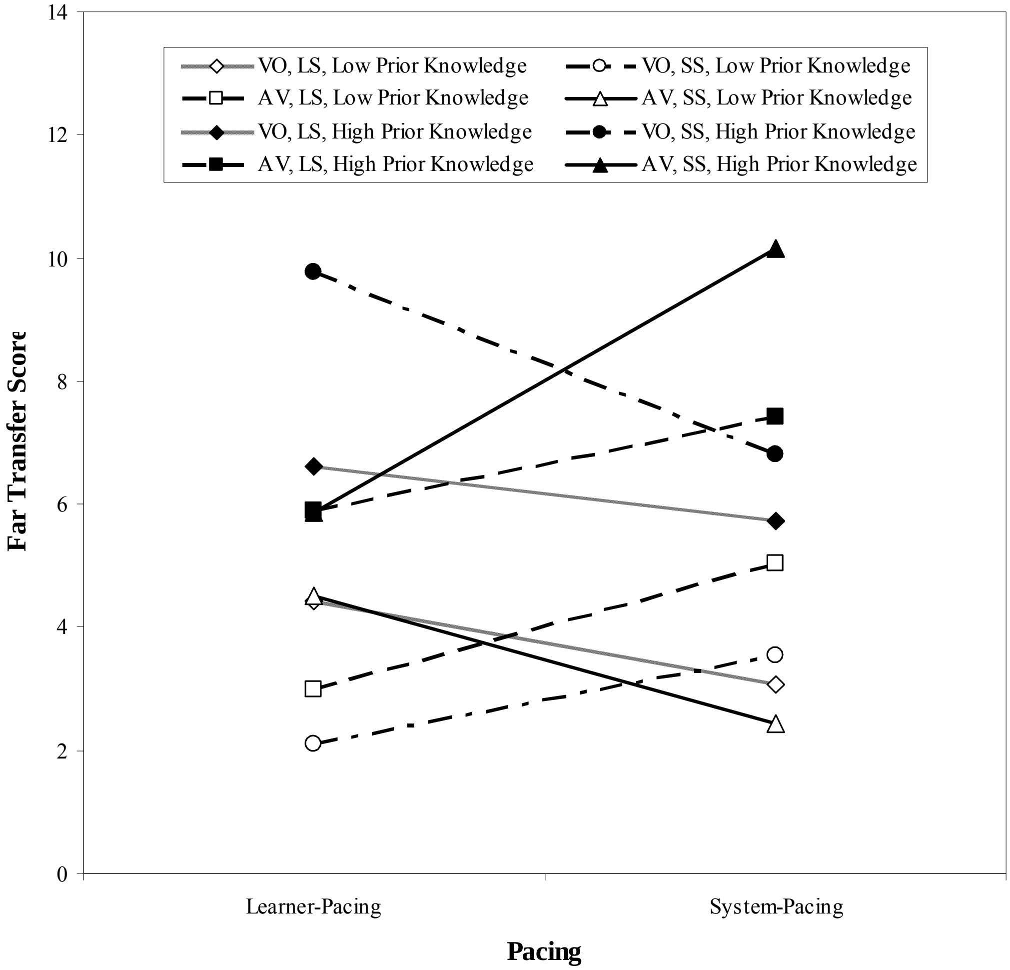

Figure 13. Simple slopes plot of the interaction between sequence-control x modality x pacing x prior knowledge. High prior knowledge and low prior knowledge indicate values one standard deviation above and below the mean pre-test score. Audio-visual is represented as AV; visual-only as VO; learner-controlled sequence as LS; and system-controlled sequence is represented as SS.

($\beta = .612$; $t(76) = 6.995$; $p < .001$), there was a modality x pacing interaction ($\beta = -1.393$; $t(76) = -3.367$; $p = .001$; see Figure 14) and a modality x pacing x pre-test score interaction ($\beta = 1.561$; $t(76) = 3.758$; $p < .001$; see Figure 15). Figure 14 shows a modality x pacing interaction similar to the one achieved for high prior knowledge learners. However, the interaction in Figure 14 is not as strong because it is influenced

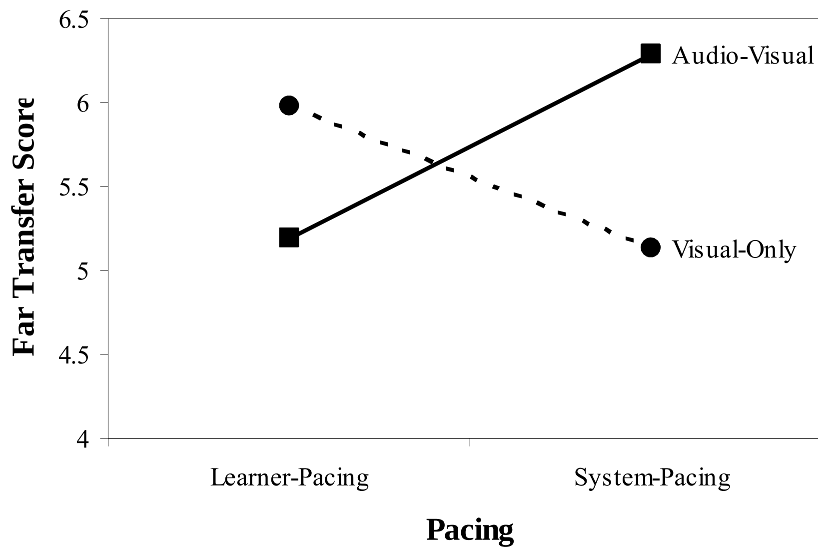

Figure 14. Interaction plot for modality x pacing under system-controlled sequencing.

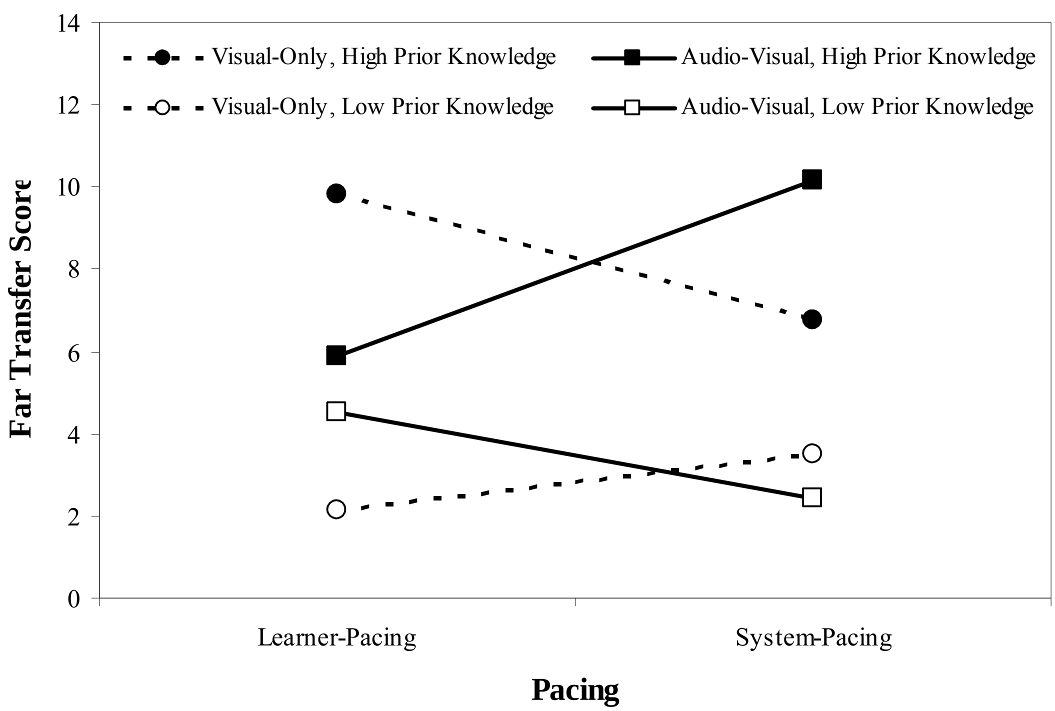

Figure 15. Simple slopes plot of the interaction between modality x pacing x prior knowledge. High prior knowledge and low prior knowledge indicate values one standard deviation above and below the mean pre-test score.

by the low prior knowledge scores as well. From Figure 15, it seems that the modality effect was well- supported for high prior knowledge learners under system-pacing conditions (audio-visual conditions tended to outperform visual-only conditions). However, the modality effect reversed under learner-pacing conditions. For low prior knowledge learners, there was also a pacing x modality pattern, though much less prominent. The pattern for low prior knowledge learners showed that, under system-pacing conditions, they tended to perform better on far transfer scores when learning from written text and diagrams (reverse modality effect). However, under learner-pacing conditions, the modality effect was supported, with low prior knowledge participants tending to achieve higher far transfer scores when learning from narration and diagrams.

Chapter 5: Discussion

Introduction

This study examined three research questions regarding modality, interactivity and the effects of mathematics anxiety when learning from a computer program designed to teach division with fractions.

The first research question set out to determine the relationships between mathematics anxiety, engagement, mental effort, pre-test, and post-test scores. I hypothesized that mathematics anxiety would be negatively correlated with engagement, pre-test, and post-test scores, and positively correlated with mental effort. The first research question also examined to what extent mathematics anxiety, engagement, mental effort, and pre-test scores predict learning outcomes.

The second research question investigated the impact of the modality principle under conditions that varied in the amount of control afforded to the learner. In accordance with research supporting the modality principle, my hypothesis was that participants learning from diagrams and narration would produce better learning outcomes than participants learning from diagrams and written text when the computer program was presented in a traditional system-paced, system-sequenced format. However, I also predicted that under learner-control, the modality effect found frequently in system-controlled experiments would disappear.

The third and final research question aimed to examine whether mathematics anxiety and prior knowledge interact with modality, pacing or sequence-control.

This chapter is structured to further examine the results of this study in the context of the three research questions. The implications of this study on multimedia learning will also be investigated. The discussion will conclude with the limitations of the thesis, and possible directions for future research.

Research Question 1: Examining Relationships among Mathematics Anxiety, Engagement, Mental Effort, Pre-test Scores, and Learning Outcomes

Mathematics Anxiety and Mathematics Performance

Not surprisingly, and as predicted in my hypothesis, mathematics anxiety was negatively correlated with pre-test scores and post-test scores. Performance scores have long been examined in relationship to mathematics anxiety, and the findings have consistently shown that highly mathematics-anxious students perform worse on standardized mathematics tests than low mathematics-anxious students (Hembree, 1990). The avoidance behaviour exhibited by many highly mathematics-anxious students may be partially to blame for the discrepancies in achievement, as these students tend to take fewer mathematics courses, and, as a result, they learn less than their low mathematics-anxious counterparts (Ashcraft, 2002). Ashcraft has also mentioned that the relationship between mathematics anxiety and mathematics achievement makes it difficult to interpret the poor performance scores obtained in empirical studies. When highly mathematics-anxious students perform poorly on a computational task, it is not always clear whether the poor performance is a result of a low level of mathematics competency or a high level of mathematics anxiety. However, in a meta-analysis by Hembree, the research showed that, when provided with behavioural treatment for mathematics anxiety, highly mathematics-anxious students' achievement scores increased to a level that was comparable to their less mathematics-anxious peers. These findings indicate that mathematics anxiety contributes to the poor performance outcomes of highly mathematics-anxious individuals.

Mathematics Anxiety and Engagement

In agreement with the hypothesis, this study revealed a significant negative correlation between mathematics anxiety and engagement with the instructional computer program. As with mathematics achievement, attitudes towards mathematics have also been studied in relation to mathematics anxiety. Hembree (1990) demonstrated in his meta-analysis that highly mathematics-anxious students enjoy mathematics less, and they have less motivation and lower self-confidence when it comes to taking mathematics courses. These extremely negative attitudes adopted by mathematics-anxious individuals can help to explain the negative correlation between engagement and mathematics anxiety found in my results. It has also been reported that some mathematics-anxious students exhibit avoidance behaviour while participating in experiments requiring them to complete computation-based tasks (Ashcraft & Faust, 1994). These students tend to rush through the experiment in order to complete it as quickly as possible, and to presumably relieve themselves of the anxiety reaction. It is possible that this avoidance behaviour, combined with generally poor attitudes towards mathematics, may have contributed to the low levels of engagement reported by mathematics-anxious students in this study.

Mathematics Anxiety and Mental Effort

As predicted, a significant positive correlation between mathematics anxiety and mental effort was obtained in this study. There are at least two possible theoretical explanations for this relationship. First, the learner's lack of competency in mathematics could be contributing to the increased mental effort. As described earlier, the results from this study showed a strong negative correlation between pre-test scores and mathematics anxiety. Students with high levels of mathematics anxiety performed more poorly on the fractions pre-test. If the poor performance is a reflection of the mathematics-anxious students' prior knowledge (and not their high levels of mathematics anxiety), then it is possible that these students have fewer mathematics-related schemas in their long-term memory than their more high-achieving peers. Since schemas assist in the reduction of intrinsic cognitive load, students with higher levels of prior knowledge (and consequently more well-developed schemas) will experience lower levels of cognitive load when processing incoming information. If the mathematics-anxious students do indeed have lower levels of prior knowledge, then we can speculate that their greater mental effort scores reflect an increased cognitive load compensating for a lack of well-developed mathematics-related schemas.

Although the previous explanation is plausible, it fails to take into account the detrimental effect of mathematics anxiety on working memory capacity (Ashcraft & Kirk, 2001). As described in the literature review, intrusive thoughts and worry caused by the anxiety reaction can consume working memory resources, leaving fewer resources available for processing incoming information (Eysenck & Calvo, 1992). As a result, anxious individuals are more likely to experience a cognitive overload, as they must attend to both the anxiety reaction and processing incoming information at the same time. From this account, it is not surprising that highly mathematics-anxious students reported greater levels of mental effort than low mathematics-anxious students when learning from the instructional computer program.

As the previous two paragraphs have demonstrated, there are at least two possible theoretical explanations for the positive correlation between mathematics anxiety and mental effort. It is possible that the low pre-test scores attained by the mathematics-anxious students reflect a lower level of prior knowledge, thus resulting in their experience of a greater intrinsic cognitive load relative to their higher-scoring peers. However, it is also a possibility that the high and low mathematics-anxious students have similar levels of prior knowledge, and the pre-test scores achieved by the mathematics-anxious students are lower due to interference from the anxiety reaction. If this is the case, then the relationship between mathematics anxiety and mental effort can be explained by the extraneous cognitive load experienced by mathematics-anxious students coping with the anxiety reaction. However, it must be noted that, due to the nature of this study, we can only speculate as to whether mathematics anxiety, prior knowledge or perhaps a combination of both contributed to the low pre-test scores and high levels of mental effort experienced by the mathematics-anxious individuals.

Mathematics Anxiety, Pre-test Scores, Mental Effort, and Engagement as Predictors for Learning Outcomes

When mathematics anxiety, pre-test scores, mental effort, and engagement were entered into a simultaneous regression analysis to predict post-test outcomes, only pre-test scores and engagement were significant predictors. Although individually each independent variable could account for a significant proportion of the variance of the post-test scores, the results from the multiple regression analysis demonstrated that some of the predictors accounted for the same variance of the outcome variable. Mathematics anxiety, for example, has a significant negative relationship (r = -.429) with the post-test scores, and individually accounts for 18.4% of the variance of the outcome variable. However, the multiple regression analysis showed that when engagement, pre-test scores, and mental effort were held constant, mathematics anxiety was no longer a significant predictor of learning outcomes. This finding was not altogether surprising, as mathematics anxiety was also significantly correlated with each of the three other predictor variables.

Summary of Research Question 1

The results from this study supported all hypotheses from the first research question. The analysis showed that mathematics anxiety was negatively correlated with pre-test scores, post-test scores, and engagement. This was not a surprising outcome, as previous research has shown that highly mathematics-anxious individuals perform more poorly on mathematics-related achievement tests, and have less motivation in mathematics-related domains (Hembree, 1990). Additionally, highly mathematics-anxious students also reported higher levels of mental effort when learning from the instructional computer program. It is possible that this increased cognitive load could have resulted from a lower mathematical competency, or worrisome and intrusive thoughts consuming the working memory resources.

Finally, a regression analysis with mathematics anxiety, pre-test score, mental effort and engagement entered as the independent variables predicted 43% of the variance of the post-test score. However, only pre-test score and engagement were significant predictors in the analysis.

The above discussion points to the troubling relationship between mathematics anxiety and mathematics achievement. The research has shown that the intrusive thoughts and worry caused by mathematics anxiety can have a crippling effect on students' performance outcomes. Additionally, students with mathematics anxiety tend to have negative attitudes towards mathematics, and thus avoid taking elective courses in mathematics.

As the participants in this study were elementary teacher candidates, there are additional concerns to be addressed. Not only does mathematics anxiety affect the teacher candidates' attitudes and performance, but it is also possible that their anxiety may influence their approach to teaching mathematics. Teachers with high levels of mathematics anxiety may have significant difficulty teaching the subject with enthusiasm and excitement (Wood, 1988). This fact makes the study of mathematics anxiety within the teacher candidate population even more important to address. Understanding how mathematics anxiety is manifested, and how it can be alleviated, may enable highly mathematics-anxious teacher candidates to approach the teaching of mathematics with a more positive attitude and a greater sense of confidence.

Research Question 2: The Modality Principle Under System and Learner Control

The Modality Principle Under System-Pacing

As predicted, the modality effect was observed under the system-pacing condition. Under this condition, participants learning from diagrams and narration outperformed participants learning from diagrams and written text on the post-test far transfer questions. According to Cognitive Load Theory (Paas et al., 2003; Sweller, 2005) and the Cognitive Theory of Multimedia Learning (Mayer, 2001, 2005), the modality effect occurred because participants in the audio-visual condition processed the instructional materials through both the visual channel and auditory channel simultaneously. This resulted in an increase of working memory resources compared to participants in the visual-only condition, who were required to process all incoming information through the visual channel alone. It is possible that participants in the audio-visual condition achieved higher learning outcomes because they were able to use the available learning time more efficiently. With limited time to attend to the learning materials under system-paced conditions, it was important for participants to process and integrate the information rather quickly. Participants in the audio-visual condition had an advantage because they could listen to the narration and attend to the diagram at the same time. However, participants in the visual-only condition had to split their attention between both the written text and diagram. It is possible that, due to a more efficient use of time attending to the learning materials, participants in the audio-visual condition consequently were able to devote more time to other cognitive processes (such as germane processing), thus enabling them to achieve deeper learning.

The results did not show a modality effect for retention and near transfer questions. As explained by Harskamp, Mayer and Suhre (2007), this may be due to the relative amount of extraneous cognitive load experienced by participants in the visual-only condition. When instructional materials have a moderate amount of extraneous load, the participants only have enough working memory resources to deal with extraneous and intrinsic processing. In this case, germane processing does not occur, and the result is rote learning. Participants learning under these conditions generally perform well on retention questions, but they also perform poorly on transfer questions. It is possible that this is what occurred in the system-paced, visual-only condition of this study, and as a result the modality effect was only significant when the participants answered the far transfer questions.

The Modality Principle Under Learner-Pacing

As I hypothesized, the modality effect disappeared when participants could control the pace of instruction. Under learner-pacing, participants in the visual-only condition performed marginally better on far transfer questions than participants in the audio-visual condition (M = 5.66, SD = 3.72 in visual-only versus M = 4.81, SD = 3.58 in audio-visual), but the difference was not significant. The results demonstrated that the modality principle lost its effectiveness under the learner-paced conditions, resulting in a nullification of the effect. Without the fixed time constraints of system-paced learning environments, participants in the learner-paced condition could take as much time as they needed to process the learning materials, and integrate the information into long-term memory. As a result, participants in the audio-visual condition no longer held an advantage over the participants in the visual-only condition by being able to attend to the narration and diagrams simultaneously. Participants in the visual-only condition could compensate for the split-attention between the written text and diagrams by spending as much time as they required to process the information before proceeding to the next slide.

The Modality Principle and Control of Sequence

The results from this study showed that control of sequence did not have an impact on the effectiveness of the modality principle. The lack of any significant finding could be a result of some participants in the learner-controlled sequence condition not taking advantage of this feature. Upon inspecting the data files that recorded the viewing sequence of the slides for each participant, it was found that some participants in the learner-controlled sequence condition approached the program in a very serial manner. These participants started with the first lesson, and progressed through to the last lesson without backtracking to previous lessons or slides. Consequently, they ended up viewing the program in a manner that almost mirrored the sequencing of those in the system-controlled sequence condition. As a result, it is not surprising that no significant effects were found.

The Modality Principle and Learning Time

The amount of time spent learning the concepts described in the instructional computer program was recorded to see if it had any impact on the post-test scores. If any one treatment condition produced superior learning outcomes, it would be important to know if the better performance scores were potentially a result of more time spent learning the concepts. However, it seems that this was not the case. As expected, the mean learning time in the four different system-paced conditions was nearly identical, with the mean time ranging from 34.7 minutes to 35.8 minutes (see Table 8). With learner-pacing, there was a greater range of mean learning times. In particular, the two visual-only conditions had much lower mean learning times than the two audio-visual conditions. The two audio-visual conditions had learning times similar to the system-paced conditions (35.3 minutes for system-controlled sequencing and 38.3 minutes for learner-controlled sequencing). However, the participants in the visual-only, learner-paced conditions had the lowest mean learning times (28.5 minutes for system-controlled sequencing and 26.8 minutes for learner-controlled sequencing). The variance within each learner-paced condition was greater than the system-paced conditions, as some students progressed through the program very rapidly, and others took significantly longer. The non-significant relationship between learning time and post-test score, combined with the fact that six of the eight treatment conditions had very similar learning times and participants in the other two treatment conditions took less time to complete the program, but achieved similar learning outcomes, indicates that more time spent learning the program did not translate into higher learning outcomes. Consequently, the superior performance of any one treatment condition could not be attributed to increased learning time.

The Modality Principle and Mental Effort

In accordance with previous studies examining the modality principle and subjective mental effort (e.g., Tabbers, 2002; Tabbers et al., 2001; Tindall-Ford et al., 1997), a significant effect of modality was found in this study. Participants in the visual-only condition reported significantly higher levels of mental effort than participants in the audio-visual condition in both the learner-pacing and system-pacing conditions. According to Cognitive Load Theory and the Cognitive Theory of Multimedia Learning, this effect is due to the fact that participants in the visual-only condition were required to process all incoming information through the visual channel. As a result, the auditory channel was left unused, and the visual channel was overloaded as it was required to process both the diagrams and written text. However, Tabbers has suggested an alternative explanation for the increased mental effort by visual-only participants. Tabbers stated that participants in visual-only conditions experience greater cognitive load because they must alternate between looking at the diagrams and written text. In other words, when learning from written text and diagrams, participants must read some text, hold it in working memory, switch to the diagram, find the appropriate section of the diagram related to the text, and mentally integrate the two pieces of information before reading the next line of text. This process of holding written text in the working memory while searching for the appropriate part of the diagram is thought to consume more working memory resources than looking at a diagram while simultaneously listening to narration. It is interesting to note that, even under learner-pacing, visual-only conditions required more mental effort than audio-visual conditions. This result is inconsistent with the explanation of cognitive load and learner-pacing from Harskamp et al. (2007). They argued that students in learner-pacing conditions have as much time as they require to adequately review the instructional materials; thereby reducing extraneous cognitive load in visual-only conditions. If this were the case in the current study, one would have expected lower mental effort scores in the learner-pacing, visual-only condition. The discrepancy between the results in this study, and Harskamp et al.'s explanation, may be due to participants in the visual-only, learner-pacing condition spending the least amount of time learning the instructional program. Consequently, it is possible that participants in this condition did not frequently review the instructional materials, and as a result they experienced a higher level of mental effort than would have been expected if they had spent more time learning the program.

Summary of Research Question 2

This study provides support for the modality principle in system-paced conditions. However, under learner-paced conditions, the results indicate that there was no modality effect. In fact, participants in the visual-only, learner-paced condition performed marginally better than those in the audio-visual, learner-paced condition, although the difference was not significant. Control of sequence did not impact the effectiveness of the modality principle. This may have been due to the fact that participants in all sequencing conditions proceeded through the program in a serial manner with limited backtracking. An effect of modality was reported for ratings of subjective mental effort, with participants in the visual-only condition requiring greater mental effort than participants in the audio-visual condition. No relationship was found for learning time and post-test score, although participants in the visual-only, learner-paced condition took less time to complete the program. This was presumably a result of their ability to skim through written text quickly—an option not available to participants in any of the other conditions.

Research Question 3: Examining how Mathematics Anxiety and Prior Knowledge Interact with Format of Instruction.

The Effect of Mathematics Anxiety with Format of Instruction

Two significant interactions involving AMAS score were found in an ATI with mathematics anxiety as the aptitude factor and modality, pacing, and sequence-control as the treatment factors. These two interactions are discussed below.

Interaction 1: AMAS score x modality x pacing. With far transfer score as the dependent variable, a significant interaction was obtained for mathematics anxiety, modality, and pacing. A simple slopes plot provided a visual representation of how mathematics anxiety interacts with the modality effect. Participants with high levels of mathematics anxiety (i.e., those who scored one standard deviation above the mean AMAS score) performed poorly in all conditions of pacing and modality. As a result, the modality effect was not achieved in either learner-pacing or system-pacing conditions for these participants. The lack of a modality effect may be related to the highly mathematics-anxious participants reporting higher levels of mental effort when learning the concepts from the instructional computer program. The greater mental effort score could possibly be attributed to lower levels of prior knowledge or worrisome thoughts consuming the working memory resources. Both of these explanations are plausible, and both would contribute to higher levels of cognitive load. It may be the case that the cognitive load (whether it was resulting from a low level of prior knowledge, or a high level of anxiety) of the highly mathematics-anxious participant was so great that none of the available formats of instruction could sufficiently reduce the cognitive load to a level that would allow deep learning to occur.

In contrast to the highly mathematics-anxious participants, modality and pacing had a greater impact on the far transfer scores of low mathematics-anxious (i.e., those who scored one standard deviation below the mean AMAS score) participants. For low mathematics-anxious participants in the system-pacing condition, the modality effect was supported with participants in the audio-visual condition tending to achieve higher far transfer scores than participants in the visual-only condition. However, the modality effect reversed under learner-pacing, with participants in the visual-only condition tending to perform better on far transfer questions than participants in the audio-visual condition.

The modality and pacing interaction observed in the low mathematics anxiety condition may have been related to the lower levels of mental effort reported by low mathematics-anxious participants. While highly mathematics-anxious participants may have experienced excessive cognitive load that prevented deep learning from occurring in any condition, low mathematics-anxious participants may have experienced only low to moderate levels of cognitive load. Consequently, the intrinsic cognitive load experienced by the low mathematics-anxious participants may have been low enough to allow germane processing to occur when extraneous cognitive load was minimized, but also sufficiently high enough that germane processing was hindered when they were required to deal with extraneous cognitive load resulting from the design of a particular instructional format. A similar explanation was provided by Harskamp et al. (2007) when they found that students learning from diagrams and narration performed significantly better on transfer questions than students learning from diagrams and written text, but there was no significant difference between groups regarding performance on retention questions. Harskamp et al. argued that students in the diagrams and written text experienced higher levels of extraneous load as a result of processing all information through the visual channel. This left fewer resources available for intrinsic and germane processing. Because intrinsic cognitive load is processed before germane cognitive load, and in this situation the intrinsic cognitive load was sufficiently high enough to consume the remaining working memory resources, there were no resources left over for germane processing, and consequently deep learning did not occur (as demonstrated by the poor transfer scores). However, as the participants processed the intrinsic cognitive load, they paid attention to the learning materials; this resulted in rote learning, and good retention scores. Participants from the diagrams with narration condition benefitted from the reduced extraneous cognitive load of the dual modality condition. Because of the reduced extraneous load, they had more working memory resources available for intrinsic and germane processing, and consequently they achieved good scores on both retention and transfer questions.

The results and argument reported by Harskamp et al. (2007) helped to explain the impact of both intrinsic and extraneous cognitive load on learning outcomes in various modalities. Learners have limited amounts of available working memory resources for processing information. When intrinsic cognitive load is low to moderate, as was likely the case with the low mathematics-anxious participants, germane processing can occur when extraneous load is minimized. However, when these learners must process extraneous load resulting from the design of the instructional materials, the sum of the two cognitive loads (extraneous and intrinsic) may be too high to allow for germane processing to occur.

Interaction 2: AMAS score x sequence-control. The second significant interaction involved mathematics anxiety and sequence-control, with far transfer score as the outcome variable. The simple slopes plot showed an interesting pattern, with highly mathematics-anxious participants performing rather poorly in both sequencing conditions, and low mathematics-anxious participants in system-controlled sequence conditions performing relatively well when compared to low mathematics-anxious participants in the learner-controlled sequence conditions. It is not entirely clear what may have caused this effect for low mathematics-anxious participants, especially considering that many participants in the learner-controlled sequence condition seemed not to take advantage of the extra control afforded by the feature. In a future study, it may be valuable to analyze the sequencing patterns of low mathematics-anxious participants in order to better understand the effect.

There is at least one explanation that may account for low mathematics-anxious participants performing more poorly in the learner-controlled sequence condition. As described by Shapiro and Niederhauser (2004), increases in learner-control can augment cognitive load as a result of the metacognitive demands incurred when navigating an interactive environment. It may be the case that the learner-controlled sequencing condition was a source of extraneous cognitive load due to the metacognitive demands of the condition. Learner-controlled sequencing did not have a negative impact on highly mathematics-anxious learners, but this may be a result of their scores already being so low (mean scores were between three and five out of a possible 15 points). Further research is required to fully understand the contributing factors to this interaction, as it is possible that the interaction is a result of a significant spurious correlation.

The Effect of Prior Knowledge with Format of Instruction

Three significant interactions involving pre-test score were found in an ATI with prior knowledge as the aptitude factor, modality, pacing, and sequence-control as the treatment factors, and far transfer score as the dependent variable. These three interactions are discussed in further detail below.

Interaction 1: Prior knowledge x modality x pacing. A significant interaction was obtained for prior knowledge, pacing, and modality. As was the case with the previous interactions, a simple slopes plot was created to provide a visual representation of the interaction. The plot revealed an interaction that was very similar to the AMAS score x modality x pacing interaction described previously. As with the highly mathematics-anxious participants, participants with low levels of prior knowledge tended to perform poorly on questions of far transfer in all treatment conditions. The far transfer scores achieved by the high prior knowledge learners also tended to parallel the far transfer scores attained by the low mathematics-anxious participants. Under system-pacing, a modality effect for high prior knowledge participants was obtained, with those in the audio-visual condition tending to perform better on far transfer questions than those in the visual-only condition. Under learner-pacing, the pattern reversed, with high prior knowledge participants tending to perform better under visual-only conditions.

This is another case in which cognitive load may explain the differences in interactions for high prior knowledge participants and low prior knowledge participants. Participants with low levels of prior knowledge most likely did not possess the required schemas to effectively process the instructional materials. As a result, they may have experienced a heavy cognitive load in all conditions, and were unable to perform well on the far transfer questions. The high prior knowledge learners most likely experienced only a moderate amount of cognitive load due to a more well-developed set of schemas in long-term memory. Consequently, they had sufficient working memory resources available for germane processing when extraneous cognitive load was minimized.

The similarities between the AMAS score x pacing x modality interaction and the prior knowledge x pacing x modality interaction is likely a direct result of the significant correlation between mathematics anxiety and prior knowledge. The high prior knowledge participants tended to report lower levels of mathematics anxiety, and the participants with low levels of prior knowledge tended to report higher levels of mathematics anxiety. Because the two interactions are so similar, it is difficult to ascertain exactly how mathematics anxiety individually contributes to the interaction, considering the amount of research that already recognizes the significant impact of prior knowledge to learning outcomes in multimedia instruction.

Interaction 2: Prior knowledge x sequence-control. A second significant interaction involved prior-knowledge and sequence-control, with far transfer score as the outcome variable. The simple slopes plot showed a pattern with low prior knowledge participants tending to achieve poor far transfer scores in both sequencing conditions. The high prior knowledge participants tended to score higher on far transfer questions in the system-controlled sequence conditions, rather than the learner-controlled sequence conditions.

The prior knowledge x sequence-control interaction also paralleled the AMAS score x sequence-control interaction. As was the case with AMAS score, it is not clear what caused this interaction. The metacognitive demands of learner-control may be the reason behind the poorer performance of the high prior knowledge participants in the learner-controlled sequence condition. It is possible that the effect did not transfer over to the low prior knowledge learners because they were already experiencing a floor effect on transfer scores. However, as the previous research is limited, more studies are required before definitive conclusions can be reached regarding the interaction between sequence-control and prior knowledge.

Interaction 3: Prior knowledge x sequence-control x pacing x modality. A four-way interaction was discovered that included all treatment factors and prior knowledge. To better understand the interaction, a simple effects approach was taken to analyze modality, pacing and prior knowledge under each of the sequence-control conditions. Only under the system-controlled sequencing condition were further interactions uncovered (modality x pacing; modality x pacing x prior knowledge). Although difficult to interpret, there are a few points worth mentioning regarding the four-way interaction.

First, all far transfer scores achieved by high prior knowledge participants were higher than the far transfer scores achieved by low prior knowledge participants. This shows that no treatment conditions were able to "level the playing field" regarding the learning outcomes of the study. Second, the four-way interaction also demonstrated, with the assistance of a simple effect approach, that there was a strong modality x pacing interaction among high knowledge participants in the system-controlled sequencing condition. This interaction supported the argument for a modality effect under system-pacing, and a reverse modality effect under learner-pacing (see Tabbers, 2002). The same interaction pattern was observed for high prior knowledge participants in the learner-controlled sequence condition, but it was very weak in comparison.

Among low prior knowledge participants, there was no support for a modality effect in system-paced conditions. Although there was a very weak pattern supporting the modality x pacing interaction achieved in Tabbers (2002) under the learner-controlled sequence condition, another weak pattern showing the modality x pacing interaction in the opposite direction was found in system-controlled sequencing condition. Considering that the patterns observed among the low prior knowledge learners were all very weak, more studies need to be conducted before any solid conclusions can be reached.

Summary of Research Question 3

Two significant interactions involving mathematics anxiety and format of instruction were observed, and three significant interactions involving prior knowledge and format of instruction were found.

Both interactions involving mathematics anxiety suggested that highly mathematics-anxious participants tended to score poorly on far transfer questions in all treatment conditions. Low mathematics-anxious participants seemed to be more greatly affected by the treatment condition to which they were assigned. However, considering that (a) mathematics anxiety and prior knowledge are significantly correlated; and (b) similar interactions were found for both prior knowledge and mathematics anxiety, it is not clear whether mathematics anxiety interactions are a consequence of mathematics competency or mathematics anxiety.

The prior knowledge x modality x pacing interaction provided further evidence of the joint effect of prior knowledge and modality. Prior knowledge can have an impact on whether or not the modality effect occurs. When learning new information, participants with very low prior knowledge may experience a level of intrinsic cognitive load so heavy that audio-visual materials cannot sufficiently reduce the overall cognitive load to allow for deep learning to occur. However, participants with higher levels of prior knowledge may be able to benefit from the reduced cognitive load of audio-visual materials in system-pacing conditions.

The results from this study further emphasize the need to understand how individual differences interact with the modality effect. The four-way interaction demonstrates how minor changes in an instructional format, combined with varied degrees of prior knowledge, might have a significant impact on learning outcomes. We need to further research these interactions to better understand when the modality principle should, or should not, be applied.

Limitations

The limitations of this study can be grouped into three categories: (a) experimental design issues; (b) individual differences; and (c) validity of the measuring instruments. The following sections address the limitations of this experiment in detail.

Experimental Design Issues

One of the goals of this study was to situate the experiment in an authentic classroom environment. Although the experiment took place during the participants' regularly-scheduled class period, and the instructional materials were related to the course materials, there were certain aspects of the experiment that would not be considered typical classroom activity. In particular, the participants were presented with an instructional program, followed immediately by a post-test to assess what they had learned in the previous hour. Considering the amount of material covered in the instructional program, it might have been better to separate the program into smaller sections, and spread them out over two or three classes. Additionally, with the administration of the post-test immediately following the instructional session, there was no way of knowing if the modality principle would have any long-term effects on the learning outcomes. Without a clear understanding of the long-term consequences of the modality principle, it is more difficult to determine when exactly it should be applied. This is especially the case now that there is preliminary research suggesting a reversal of the modality effect when testing is delayed by one week (Segers, Verhoeven & Hulstijn-Hendrikse, 2008).

Individual Differences

Although I controlled for prior knowledge to the best of my ability with a pre-test and stratified random sampling, the differences between the novice and expert learners were extreme. As a result, the design of the instructional computer program was a difficult task. In order to produce a modality effect, it was essential to create a program that was sufficiently demanding of the cognitive resources. However, due to the variance in the prior knowledge of the participants, the program proved to be too difficult in all conditions for participants with the lowest levels of prior knowledge and highest levels of mathematics anxiety. The modality effect was most apparent among participants with higher levels of prior knowledge (relative to the rest of the sample).

Another limitation in this study concerned the engagement of the participants. As reported in the results section, some students were very engaged during the experiment and others were not engaged at all. This had an effect on the quality of the results, as some participants put significant effort into answering the post-test, and others did not. This may be due to the fact that the post-test scores had no impact whatsoever on the participants' course grades. A similar study by Tabbers (2002) revealed that when participants were paid for their time, a post-test modality effect was not observed. However, when a different set of participants completed the same program as part a course requirement, the modality effect was obtained. One explanation provided by Tabbers was that the participants completing the course requirement were more motivated to invest the effort to learn the instructional materials.

Validity of Measuring Instruments

There were limitations to the instrument used to assess cognitive load in this study. A subjective measure of mental effort, developed by Paas (1992), indirectly assessed the participants' cognitive load. Although this measure is designed to reveal perceived mental effort in a non-invasive manner, it is still not entirely clear how mental effort is related to intrinsic, extraneous, and germane cognitive load (Brünken, Plass & Leutner, 2003). Therefore, even though the measure of perceived mental effort gave an approximation to the participants' actual cognitive load, it did not carry the same validity as a measure that was both direct and objective.

Future Research

The robustness of the modality principle has been demonstrated on numerous occasions with novice students learning scientific or mathematical concepts in system-paced conditions (Ginns, 2005). However, it is important to know under what other conditions we can apply the modality principle. This study examined the modality principle under conditions that varied in the amount of control afforded to the learner. Additionally, it examined the interaction of both mathematics anxiety and prior knowledge with modality and learner-control.

There are still many questions that remain concerning the validity of the modality principle. As mentioned in the limitations, most experiments have only examined the short-term learning outcomes of the modality effect. A few experiments have investigated the long-term consequences of the modality principle, but the results thus far have been mixed. Delayed testing in a study by Chung (2008) showed that the modality effect was still present two weeks after the instructional session had been completed.

However, Segers et al. (2008) found a reverse modality effect with delayed testing in their study. The discrepancies between these two studies demonstrate that more research is required to determine the long-term effects of the modality principle.

As literature examining the expertise reversal effect has demonstrated, prior knowledge can significantly impact the effectiveness of the modality principle. However, other individual differences, particularly those that affect working memory, may interact with the modality principle. It has already been demonstrated that memory strategy skills and working memory capacity may impact the modality effect (Seufert et al., 2008). The recent study by Chung (2008) has also revealed a possible interaction between the modality principle and the degree of expertise of second language learners. In his study, Chung showed that low prior knowledge students learning Chinese as a second language produced a reverse modality effect when tested on the pronunciation of Chinese characters. However, when the second language learners became more proficient, a modality effect was obtained. Chung explained that the Chinese sounds were probably unfamiliar to the low prior knowledge learners. As a result, processing the sounds required a conscious effort, and thus negated any advantage of dual modality. These results further emphasize the need to examine individual differences and the modality principle, as it is imperative that we understand exactly which students will benefit most from the audio-visual learning environments.

The number of variables involved in teaching with multimedia materials makes research in this area particularly complex. Not only does the content of the computer program vary from one experiment to another, so does the duration, and the amount of control afforded to the learner. In addition, we also need to contend with the individual differences of the learners. As a result, no one experiment can make or break the modality principle. What we need to do is examine how far we can extend the modality principle beyond the traditional system-paced environments that have dominated the research thus far.

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APPENDIX A: PRE-TEST AND POST-TEST STATISTICS FOR EACH CLASS

Table A1. Pre-test and Post-test Descriptive Statistics For Each Class

Class Number	*N*	Pre-test Mean	Pre-test SD	Post-test Mean	Post-test SD
1	32	21.23	4.56	13.16	5.24
2	26	20.73	4.72	14.39	5.81
3	35	19.69	4.94	11.87	6.07
4	29	19.98	4.15	11.38	4.63
5	41	17.63	4.59	10.13	4.77
6	23	19.50	6.19	9.04	5.53
7	27	19.50	5.07	8.61	5.45

Table A2. Correlations Between Pre-test and Post-test Score for Each Class

Class Number	*N*	Correlation between Pre-test and Post-test
1	32	.526**
2	26	.301
3	35	.607**
4	29	.379*
5	41	.538**
6	23	.820**
7	27	.298

Note. * $p < 0.05$; ** $p < 0.01$.

APPENDIX B: DEFINITION OF DIVISION TERMS

Partition Model of Division: The partition model of division is often referred to the sharing-method of division. When we solve partition model division problems, we first begin with a set that needs to be divided into a specified number of groups. To find the answer we need to find out how much is in each group. For example, a partition model word problem for 18 ÷ 3 would be, "Anna has a box of 18 oranges. She wants to share them equally among her three friends. How many oranges will each friend receive?" This word problem begins with a set of 18 that needs to be divided into three equal-sized groups. When we find out how much is in one group, we will have the answer.

Measurement Model of Division: As with the partition model of division, to solve a measurement model division problem, we first begin with a set that needs to be divided into groups. However, in this case we know the size of one group, and we need to find out how many groups there are in total. For example, a measurement model word problem for 18 ÷ 3 would be, "Rachel has 18 apples. She needs 3 apples to bake a pie. How many pies can she bake?" This word problem begins with a set of 18, and we need to divide the set into groups of three. These types of problems are generally solved with repeated subtraction. By repeatedly subtracting three from 18, we find that there are six groups of three in 18.

APPENDIX C: REVIEW OF KEY TERMS AND FRACTIONS

Review of Key Terms

Numerator: This is the top number of a fraction. It tells us how many parts or shares we have.

Denominator: This is the bottom number of a fraction. It tells us what fractional part is being counted. If it is a 4, it means we are counting *fourths*; if it is a 6, it means we are counting *sixths.*

Dividend: This is the number being divided in a division problem. For example, in the question $8 \div 2 = 4$, the dividend is 8.

Divisor: This is the number that divides the dividend. For example, in the question $8 \div 2 = 4$, the divisor is 2.

Quotient: The answer to a division problem. For example, in the question $8 \div 2 = 4$, the quotient is 4.

Sum: The answer to an addition problem.

Product: The answer to a multiplication problem.

Appendix C (continued)

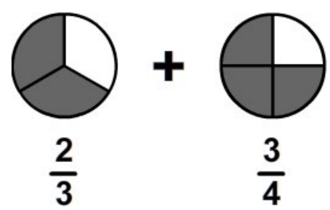
Fractions Review Sheet

This review sheet is intended to refresh your memory on some key concepts and procedures that provide a foundation for learning to divide with fractions. We will cover three topics in this review: finding a common denominator, converting improper fractions to mixed fractions and back again, and multiplying fractions.

<u>Finding a Common Denominator</u>

Finding a common denominator is required for solving many fractions problems with standard algorithms. For example, let's say we need to need to find the sum of $\frac{2}{3}+\frac{3}{4}$.

We can represent $\frac{2}{3}+\frac{3}{4}$ with the pie diagrams below:



As the diagram demonstrates, we can represent $\frac{2}{3}$ with a pie divided into thirds, since the denominator is 3. We can represent $\frac{3}{4}$ with a pie divided into fourths, since the denominator is 4. However, since both pies are divided into pieces of unequal size, it's difficult to find a solution from the diagram. If we can represent both fractions using pies with **equal-sized** parts, it will be easier to find a solution. By finding a common denominator, we can represent $\frac{2}{3}$ and $\frac{3}{4}$ using pies with equal-sized parts.

To find a common denominator, we first need to find a common multiple for the two denominators.

Multiples of 3 are: 3, 6, 9, **12**, 15, 18...

Multiples of 4 are: 4, 8, **12**, 16, 20, 24...

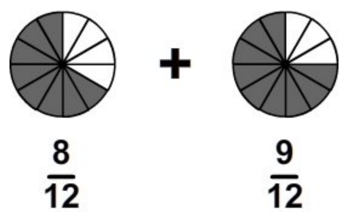
See that both 3 and 4 have a common multiple of 12. Therefore, we can set the common denominator to 12. To change $\frac{3}{4}$ into an equivalent fraction with a denominator of 12, we need to multiply both the numerator and the denominator by the same number, 3.

$$\frac{3}{4} \times \frac{3}{3} = \frac{9}{12}$$

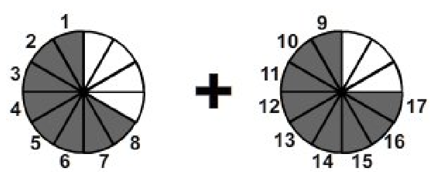
To change $\frac{2}{3}$ into an equivalent fraction with a denominator of 12, we need to multiply both the numerator and denominator by the same number, 4.

$$\frac{2}{3} \times \frac{4}{4} = \frac{8}{12}$$

Now $\frac{2}{3} + \frac{3}{4}$ can be represented as $\frac{8}{12} + \frac{9}{12}$. Since we now have a common denominator, we can represent both fractions using pie diagrams with equal-sized parts:



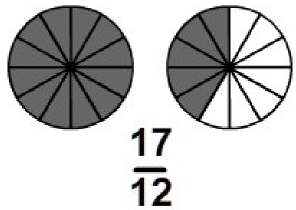
We can find the solution by calculating the total number twelfths in the problem. Counting the total number of twelfths, you can see that the answer is $\frac{17}{12}$.



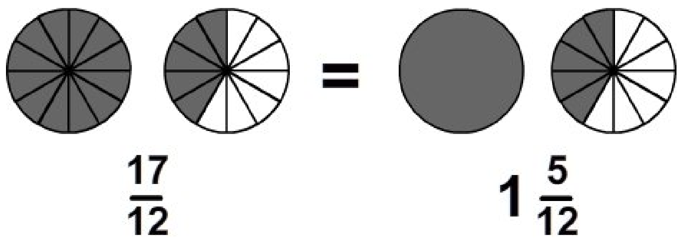
<u>Converting Improper Fractions to Mixed Fractions</u>

Continuing with the example presented above, we can review how to convert improper fractions to mixed fractions. First of all, remember that improper fractions are fractions where the numerator is greater than the denominator.

Notice how we can draw $\frac{17}{12}$ using a pie diagram.

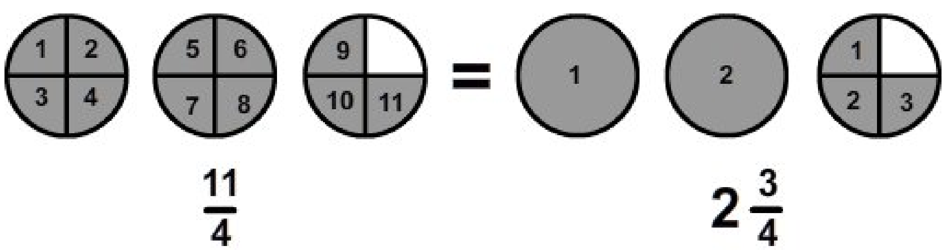


We can see that in $\frac{17}{12}$, we have one whole pie, with $\frac{5}{12}$ left over. Therefore, as demonstrated in the diagram below, $\frac{17}{12}$ is equal to $1\frac{5}{12}$.



To convert improper fractions into mixed fractions using an algorithm, we must remember that $\frac{17}{12}$ is the same as $17 \div 12$. Therefore, when we convert an improper fraction to a mixed fraction, we are finding how many times the denominator (in this case, 12) goes in to the numerator (in this case, 17). Twelve goes into 17 once, with a remainder of 5.

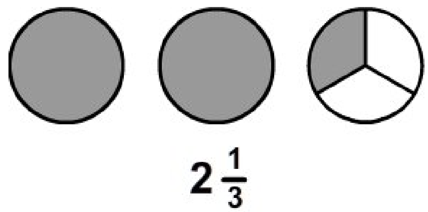
As another example, how do we convert $\frac{11}{4}$ into a mixed fraction? We need to ask how many groups of 4 are in 11. Drawing a pie diagram shows us that $\frac{11}{4}$ is equal to $2\frac{3}{4}$.



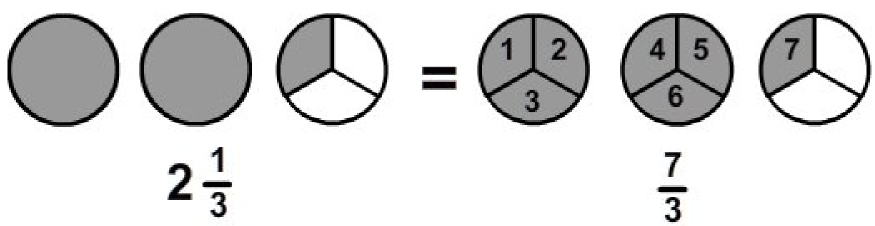
Converting Mixed Fractions to Improper Fractions

Improper fractions are particularly useful when we solve mathematical problems using standard algorithms.

To see how we convert mixed fractions to improper fractions, let's look at the example $2\frac{1}{3}$. This is a mixed fraction represented in the diagram below:



To convert $2\frac{1}{3}$ into an improper fraction, we need to divide all pies into thirds. Then we need to count the number of thirds in the $2\frac{1}{3}$. As the diagram shows, $2\frac{1}{3}$ is equal to improper fraction, $\frac{7}{3}$.



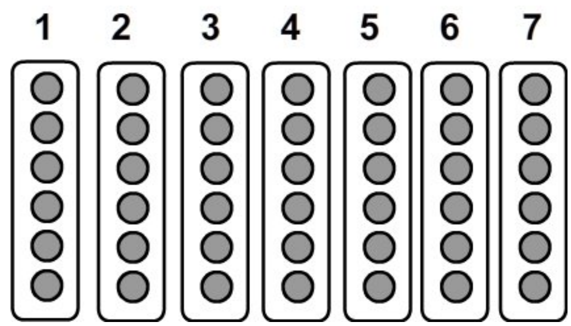
The algorithm to convert mixed fractions to improper fractions is as follows:

1. **Multiply the denominator in the fraction by the whole number.**
2. **Add that to the numerator**
3. **Then write the result on top of the denominator.**

For example, to convert $2\frac{1}{3}$ to an improper fraction using the algorithm, we first multiply 3 (the denominator) by 2 (the whole number). This results in a product of 6. Then, we add 6 and 1 (the numerator), to get a sum of 7. By placing 7 in the numerator position of the improper fraction, we find that $2\frac{1}{3}$ can be converted to an improper fraction of $\frac{7}{3}$.

Multiplying Fractions

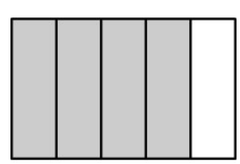
When we multiply two whole numbers, such as 7 x 6, we are finding how much is in 7 sets of 6, as the diagram shows below:



When we multiply fractions, such as $\frac{2}{3} \times \frac{4}{5}$, we are doing the same thing that we do when we multiply whole numbers. We need to find $\frac{2}{3}$ of a set of $\frac{4}{5}$. In order to make this easier to visualize, let's put it in the context of a word problem:

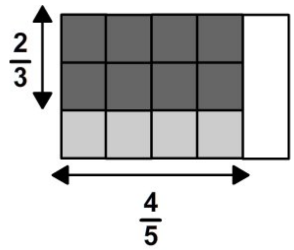
Jennifer made a batch of brownies for a bake sale. Unfortunately, she only sold $\frac{1}{5}$ *of her brownies. Therefore, she had* $\frac{4}{5}$ *of the brownies left over after the sale. Jennifer decided to give* $\frac{2}{3}$ *of the leftover brownies to her friend, Michael. How much of the whole batch of brownies did Michael receive?*

We can solve this problem using a diagram. First, we need to represent the leftover brownies, as demonstrated in the diagram below. Since $\frac{4}{5}$ of the brownies are leftover, $\frac{4}{5}$ of the diagram is shaded grey.

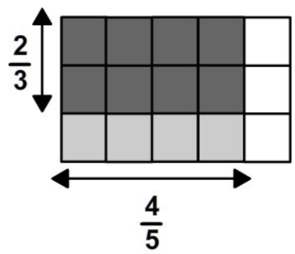


$\frac{4}{5}$

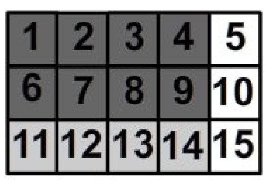
Now, Jennifer gave $\frac{2}{3}$ of the leftover brownies to Michael. As shown in the diagram below, we can colour in $\frac{2}{3}$ of the leftover brownies to show how much was given to Michael.



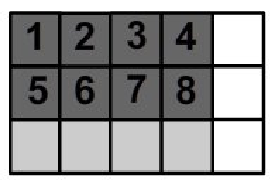
To show how much of the whole batch of brownies Michael received, we can extend the dividing lines all the way across the rectangle.



As the diagram shows below there are 15 parts in the whole batch. 8 parts of the whole batch were given to Michael. Therefore, Michael received $\frac{8}{15}$ of the whole batch of brownies.

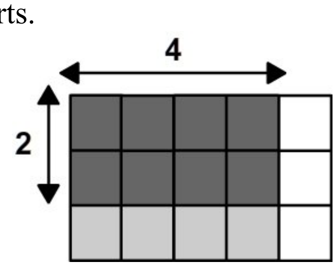


Number of parts in the whole batch of brownies

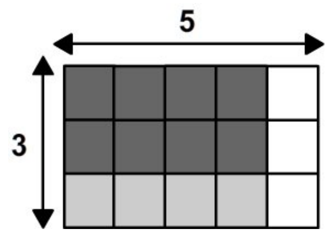


Number of parts that Michael receives

We can also solve this problem with an algorithm. Notice in the diagram below, that Michael's share of the brownies covers 4 columns and 2 rows. We multiplied 4 x 2 to find that Michael received 8 parts.



Also, notice in the diagram below that the total batch of brownies is represented by 5 columns and 3 rows. We multiplied 5 x 3 to find that the whole batch of brownies consisted of 15 parts.



Thus, this is how we came to our answer of $\frac{8}{15}$. Since the problem to solve is $\frac{2}{3} \times \frac{4}{5}$, we can find the answer by multiplying the numerators (to find the number of parts in Michael's share), and multiplying the denominators (to find the number of parts in the whole batch of brownies):

$$\frac{2 \times 4}{3 \times 5} = \frac{8}{15}$$

The general algorithm for solving multiplication problems with fractions is:

1. **Multiply the numerators**
2. **Multiply the denominators**

APPENDIX D: ABBREVIATED MATH ANXIETY SCALE

Abbreviated Math Anxiety Scale (AMAS)

For the following statements, please rate each item in terms of how anxious you would feel during the event specified. Use the following scale and circle your answer in the space to the left of the item.

1	2	3	4	5
Low Anxiety	Some Anxiety	Moderate Anxiety	Quite a Bit of Anxiety	High Anxiety

1 2 3 4 5 Having to use the tables in the back of a math book.

1 2 3 4 5 Thinking about an upcoming math test 1 day before.

1 2 3 4 5 Watching a teacher work an algebraic equation on the blackboard.

1 2 3 4 5 Taking an examination in a math course.

1 2 3 4 5 Being given a homework assignment of many difficult problems that is due the next class meeting.

1 2 3 4 5 Listening to a lecture in a math class.

1 2 3 4 5 Listening to another student explain a math formula.

1 2 3 4 5 Being given a “pop” quiz in a math class.

1 2 3 4 5 Starting a new chapter in a math book.

APPENDIX E: FINAL QUIZ

Final Quiz

Please take as much time as required to complete this quiz. Answer as many questions as you can. No calculators please, but you can refer to your review sheets if needed.

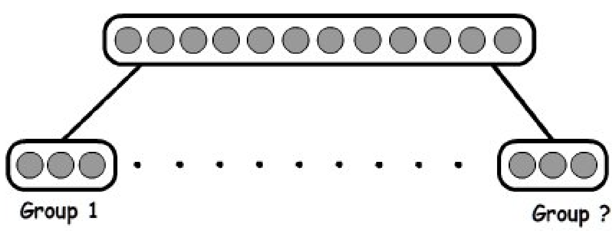
1. When we solve a **measurement** model problem, what question must we ask?

    a. How much is in one group?
    b. How much is in one whole?
    c. How many groups?
    d. Both (a) and (b)
    e. None of the above.

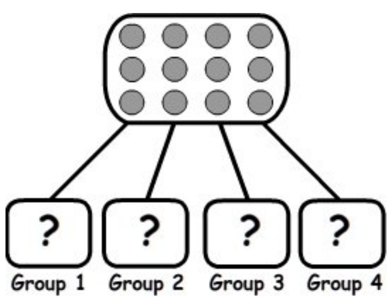
2. When we solve a **partition** model problem involving $\frac{9}{10} \div \frac{3}{4}$, what question must we ask?
    a. How much is in one group?
    b. How much is in one whole?
    c. How many groups?
    d. Both (a) and (b)
    e. None of the above.

3. Which of the following diagrams accurately depicts a **partition** model representation of
    12 ÷ 4 = ? (Multiple choice options are continued on the next page.)

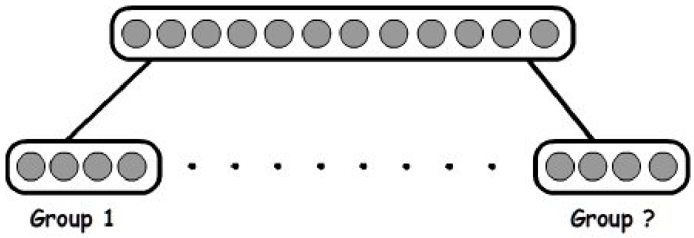
    a.



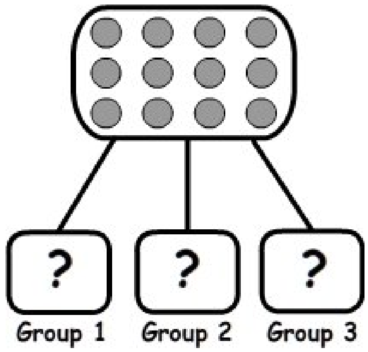
    b.



c.



d.



e. None of the above

4. Draw a **measurement** model diagram to represent: $18 \div 3 = ?$

5. Which of the following problems is a partition model word problem of $2\frac{1}{4} \div \frac{3}{4}$?

   a. Sandra has $2\frac{1}{4}$ cups of sugar. She needs $\frac{3}{4}$ of one cup of sugar to bake a batch of cookies. How many batches of cookies can she bake with her $2\frac{1}{4}$ cups of sugar?

   b. Rebecca is knitting a baby blanket. In total, the area of the blanket will be $2\frac{1}{4}$ m^2. If it takes Rebecca one day to knit $\frac{3}{4}$ m^2 of one blanket, how many days will it take her to knit the entire baby blanket?

c. While raking the leaves on his lawn, Ryan can fill $2\frac{1}{4}$ bags with dead leaves in $\frac{3}{4}$ of one hour. Continuing at this pace, how many bags could Ryan fill in one hour?

d. None of the above.

6. For the following word problem:

   Ray has 3 cups of detergent. One load of laundry requires $\frac{3}{4}$ of one cup of detergent. How many loads of laundry can Ray wash with his 3 cups of detergent?

   a. Circle the model of division that is represented in this word problem.
      1. Measurement Model
      2. Partition Model

   b. Use a **pie diagram** to find the solution. Be sure that you can see the answer from the diagram.

7. For the following word problem:

   Aidan paid $3\frac{1}{2}$ dollars for $\frac{7}{10}$ kg of tomatoes. How much would he have paid for one kilogram?

   a. Circle the model of division that is represented in this word problem.
      i. Measurement Model
      ii. Partition Model

b. Use a diagram to find the answer to the problem. Be sure that you can see the answer from the diagram.

c. Solve this problem using the invert-and-multiply algorithm.

8. For the following problem: $1\frac{3}{4} \div \frac{1}{2}$

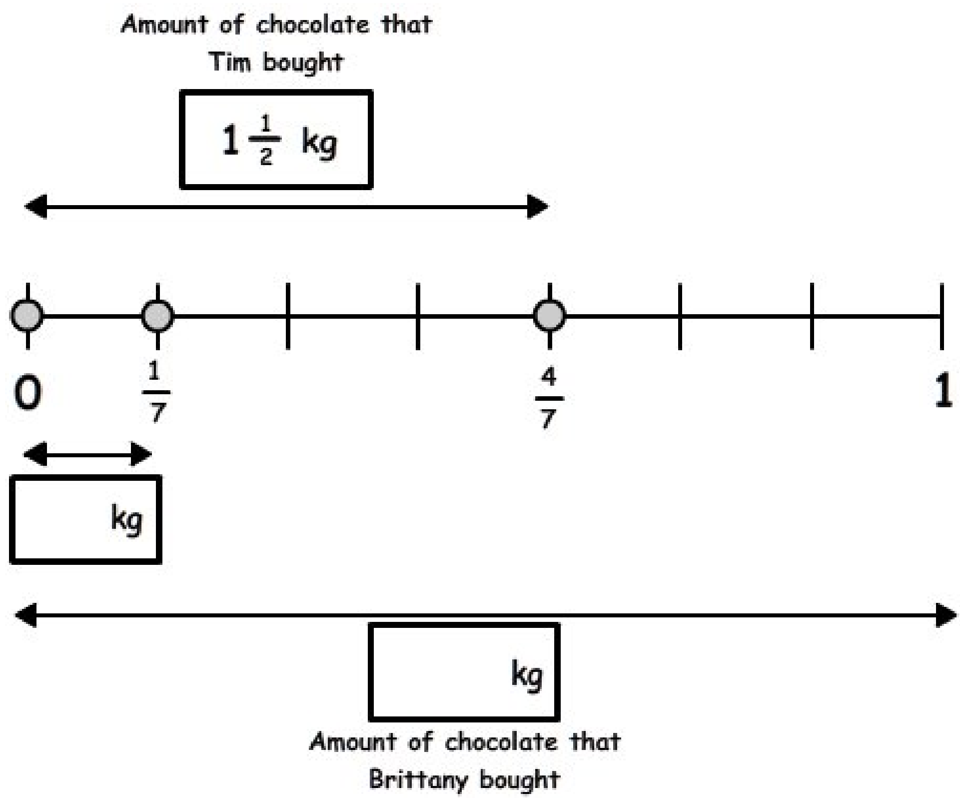
a. Write a measurement model word problem (different from other measurement problems described in this test).

b. Use a diagram to find the answer to the problem. Be sure that you can see the answer from the diagram.

9. For the following word problem:

Tim bought $1\frac{1}{2}$ kilograms of chocolate. This is only $\frac{4}{7}$ the amount of chocolate that Brittany bought. How many kilograms of chocolate did Brittany buy?

Below is a partially-completed diagram that would be used to solve this problem. Fill in the empty boxes to complete the problem.



10. For the following word problem:

Julie needs to write a 4 page psychology paper. She can write $\frac{3}{5}$ of one page in one hour. How many hours will it take her to write the entire paper?

a. Circle the model of division that is represented in this word problem.
   i. Measurement Model
   ii. Partition Model

b. Use either a pie diagram, block diagram or a number line diagram to find the answer to the problem. Be sure that you can see the answer from the diagram.

c. Solve this problem using the common denominator algorithm.

11. List the steps in the common denominator algorithm.

12. List the steps in the invert-and-multiply algorithm.

APPENDIX F: DESCRIPTIVE DATA FOR PARTICIPANTS IN ANOVA AND ATI ANALYSES

Table F1. Demographic Data

N	Females	Males	Mean Age (SD)
174	142	32	25.6 (5.1)

Table F2. Distribution of Previous Undergraduate Degrees of Participants

Previous Undergraduate Degree	*N*
Arts	81
Business	4
Social Sciences	54
Communications	1
Mathematics and Statistics	1
Physical or Life Sciences	7
Health-Related Field	2
Other	15
Multiple Majors	9

Table F3. Number of Math-Related Courses Completed in Previous Undergraduate Degree

Number of Math-Related Courses Completed	*N*
0	63
1	53
2	31
3	11
4 or more	16

Table F4. Descriptive Statistics for Nine Items on Abbreviated Math Anxiety Scale (1 – Low Anxiety to 5 – High Anxiety)

Survey Item	Mean	SD
Having to use the tables in the back of a math book.	1.85	.991
Thinking about an upcoming math test 1 day before.	3.55	1.08
Watching a teacher work an algebraic equation on the blackboard.	2.63	1.26
Taking an examination in a math course.	4.30	.998
Being given a homework assignment of many difficult problems that is due the next class meeting.	3.79	1.09
Listening to a lecture in a math class.	2.24	1.21
Listening to another student explain a math formula.	2.23	1.16
Being given a “pop” quiz in a math class.	4.02	1.12
Starting a new chapter in a math book.	1.98	1.01

Table F5. Distribution of Participants' Responses Rating their Level of Engagement

Level of Engagement	*N*
Not engaged at all	4
Not very engaged	23
Somewhat engaged	40
Fairly engaged	74
Very engaged	33

Table F6. Distribution of Participants' Responses Reporting their Perceived Difficulty of Learning the Division with Fractions Computer Program.

Level of Difficulty	*N*
Easy	20
Fairly Easy	58
Neither easy nor difficult	45
Fairly Difficult	40
Difficult	11

Table F7. Mean Mental Effort Scores (1 = very, very low mental effort; 9 = very, very high mental effort) for Participants at the End of Each Lesson

Lesson Number	*n*	Mean	Standard Deviation
Lesson 1: Key Concepts	165	3.85	1.45
Lesson 2: Measurement Model	166	5.33	1.49
Lesson 3: Partition Model	167	6.31	1.46
Lesson 4: Common Denominator Algorithm	169	4.67	1.62
Lesson 5: Invert-and-Multiply Algorithm	170	5.42	1.84

Table F8. Descriptive Statistics for Post-test Scores

Post-test Score	Mean	SD	Skewness (SE)	Kurtosis (SE)
Total score (max. score = 24)	11.14	5.28	.226 (.184)	-.549 (.366)
Retention and near transfer score (max. score = 9)	5.77	2.05	-.548 (.184)	.008 (.366)
Far transfer score (max. score = 15)	5.37	3.78	.535 (.184)	-.696 (.366)

APPENDIX G: ANALYSIS OF VARIANCE FOR TOTAL SCORE

Source	*df*	*F*	η_p^2	*p*
Sequence (S)	1	.955	.006	.330
Pacing (P)	1	.015	.000	.904
Modality (M)	1	.437	.003	.509
S x P	1	.010	.000	.921
S x M	1	.004	.000	.952
P x M	1	4.868*	.028	.029
S x P x M	1	.337	.002	.562
Error	166	(27.962)		

Note. Values enclosed in parentheses represent mean square errors. *$p < .05$.

APPENDIX H: ANALYSIS OF VARIANCE FOR RETENTION AND NEAR TRANSFER SCORE

Source	*Df*	*F*	η_p^2	*p*
Sequence (S)	1	.480	.003	.490
Pacing (P)	1	.364	.002	.547
Modality (M)	1	.067	.000	.796
S x P	1	.140	.001	.709
S x M	1	.105	.001	.747
P x M	1	1.945	.012	.165
S x P x M	1	.006	.000	.939
Error	166	(4.315)		

Note. Values enclosed in parentheses represent mean square errors.

APPENDIX I: ANALYSIS OF VARIANCE FOR FAR TRANSFER SCORE

Source	*df*	*F*	η_p^2	*p*
Sequence (S)	1	1.048	.006	.307
Pacing (P)	1	.259	.002	.611
Modality (M)	1	.539	.003	.464
S x P	1	.004	.000	.948
S x M	1	.011	.000	.916
P x M	1	5.489*	.032	.020
S x P x M	1	.716	.004	.399
Error	166	(14.192)		

Note. Values enclosed in parentheses represent mean square errors. *$p < .05$.

APPENDIX J: ANALYSIS OF VARIANCE FOR MEAN MENTAL EFFORT SCORE

Source	*df*	*F*	η_p^2	*P*
Sequence (S)	1	.208	.001	.649
Pacing (P)	1	.064	.000	.800
Modality (M)	1	5.215*	.033	.024
S x P	1	2.397	.015	.124
S x M	1	.035	.000	.851
P x M	1	.003	.000	.957
S x P x M	1	.074	.000	.786
Error	153	(1.523)		

Note. Values enclosed in parentheses represent mean square errors. $*p < .05$.

APPENDIX K: ANALYSIS OF VARIANCE FOR ENGAGEMENT SCORE

Source	*df*	*F*	η_p^2	*p*
Sequence (S)	1	.970	.006	.326
Pacing (P)	1	.180	.001	.672
Modality (M)	1	.156	.001	.693
S x P	1	.578	.003	.448
S x M	1	2.494	.015	.116
P x M	1	.023	.000	.880
S x P x M	1	.406	.002	.525
Error	166	(1.033)		

Note. Values enclosed in parentheses represent mean square errors.

APPENDIX L: ANALYSIS OF VARIANCE FOR PERCEIVED DIFFICULTY OF PROGRAM SCORE

Source	*df*	*F*	η_p^2	*p*
Sequence (S)	1	.055	.000	.815
Pacing (P)	1	1.125	.007	.290
Modality (M)	1	.228	.001	.634
S x P	1	.943	.006	.333
S x M	1	.556	.003	.457
P x M	1	1.928	.011	.167
S x P x M	1	2.746	.016	.099
Error	166	(1.234)		

Note. Values enclosed in parentheses represent mean square errors.

APPENDIX M: ATI WITH MATHEMATICS ANXIETY AS APTITUDE FACTOR AND FAR TRANSFER SCORE AS THE RESPONSE VARIABLE

Predictor Variable	*B*	*SE B*	β	*p*-value
Mean AMAS (A)	-1.587	.387	-.318	<.001
Sequence (S)	-3.473	1.184	-.921	.004
Pacing (P)	-.073	1.184	-.019	.951
Modality (M)	.090	1.184	.024	.940
S x M	.554	1.184	.147	.640
P x M	3.230	1.184	.857	.007
S x P	.712	1.184	.189	.549
S x P x M	-.894	1.184	-.236	.451
A x M	-.100	.387	-.081	.796
A x P	-.003	.387	-.002	.994
A x S	1.072	.387	.867	.006
A x S x P	-.281	.387	-.228	.468
A x P x M	-.869	.387	-.703	.026
A x S x M	-.209	.387	-.169	.589
A x S x P x M	.369	.387	.298	.341

Note. R^2 = .221.

APPENDIX N: ATI WITH PRIOR KNOWLEDGE AS APTITUDE FACTOR AND FAR TRANSFER SCORE AS THE RESPONSE VARIABLE

Predictor Variable	*B*	*SE B*	β	*p*-value
Pre-test (T)	.445	.060	.499	<.001
Sequence (S)	2.518	1.154	.668	.031
Pacing (P)	.425	1.154	.113	.713
Modality (M)	-.537	1.154	-.142	.642
S x M	.597	1.154	.158	.606
P x M	-2.134	1.154	-1.849	.066
S x P	-.592	1.154	-.157	.609
S x P x M	3.406	1.154	.898	.004
T x M	.021	.060	.110	.722
T x P	-.029	.060	-.147	.633
T x S	-.146	.060	-.753	.015
T x S x P	.029	.060	.149	.630
T x P x M	.144	.060	.745	.017
T x S x M	-.034	.060	-.174	.573
T x S x P x M	-.173	.060	-.885	.004

Note. R^2 = .333.