Self-explaining and Individual Differences in Multimedia Learning

by

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ABSTRACT

Multimodal presentations have been found to facilitate learning, however, may be a disadvantage for low spatial ability students if they require spatial visualization. This disadvantage stems from their limited capacity to spatially visualize and retain information from both text and diagrams for integration. Similarly, working memory capacity (WMC) likely plays a key role in a learner's ability to retain information presented to them via both modalities. The present study investigated whether or not the act of self-explaining helps resolve deficits in learning caused by individual differences in spatial ability, working memory capacity, and prior knowledge when learning with text, or text and diagrams. No interactions were found, but prior knowledge consistently predicted performance on like posttests. The author presents methodological and theoretical explanations as to the null results of the present study.

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Chapter 1

INTRODUCTION

Humans have a limited capacity of verbal or visual information they can encode through one channel at a time. Presenting information through more than one modality will distribute the load over multiple channels essentially freeing extra cognitive resources. This additional reserve of cognitive resources can be delegated to creating an efficient mental model and understanding of the target material. This has come to be known as the Dual-coding theory (Clark & Paivio, 1991).

However, previous studies (Mayer & Sims, 1994; Yang, Andre, & Greenbowe, 2003) found multimodal presentations to be a disadvantage for students who possess low spatial ability (SA) when the material requires mental rotation or spatial visualization for comprehension. Authors from said studies suggest that low-spatial learners must devote nearly all their cognitive resources to creating a visual representation, leaving few residual resources to utilize for integration. High spatial students have the capacity to create referential connections between the visual and verbal material (Mayer & Sims, 1994; Mayer & Moreno, 1999). Similarly, working memory capacity (WMC) likely predicts a learner's ability to retain information presented to them in more than one mode. An individual's capacity to store both visual (diagrams) and verbal (text) information can be highly indicative of students' ability to integrate said information and relate it to their personal knowledge to create connections between the two. An effective learning strategy that has been proven to serve as a metacomprehension technique (Griffin, Theide, & Wiley, 2009) that aids in filling in gaps in knowledge (Chi, De

Leeuw, Chiu, & LaVancher, 1994) has been implemented in various domains. In the present study, self-explanations were implemented with the expectation that its learning benefits surpass the learning deficits set forth by learners with low spatial ability. In order to investigate this question, a multimedia learning environment was presented to the learner containing text with or without diagrams.

Diagrams and Text in Learning

Diagrams have been shown to facilitate learning in electricity (Cheng, 2002), lighting (Serra & Dunlosky, 2010), electrical resistor systems (Marcus, Cooper, & Sweller, 1996), mechanical brakes systems (Mayer, 1989), bicycle tire pumps (Mayer & Anderson, 1991), flight principles (Fiore, Cuevas, & Oser, 2003), human respiratory system (Mayer & Sims, 1994), scientific devices (Mayer & Gallini, 1990), and physical systems (Hegarty & Just, 1993). The aid offered by diagrams in learning has been explained by various components. One of which is described as re-representational learning, where illustrations improve learning due to a repetition effect (Gyselinck & Tardieu, 1999). Another benefit of diagrams in learning is computational offloading. Computational offloading is the extent to which different external representations containing the same amount of information reduce the cognitive effort needed to extract necessary information (Ainsworth & Loizou, 2003). Larkin and Simon (1987) posit that diagrams can be more effective than sentential representations because they illustrate a series of information at a specific point on the visual, whereas the latter require a more effortful and time consuming linear search. The series of information presented at each point on a diagram allows for an explicit depiction of the relationship between the various components it demonstrates. Additionally, diagrams may explicitly depict information that at times is only implicit through textual representation, which also reduces learner's computational effort.

Different theories provide insight as to the processes occurring when obtaining information from diagrams. For processing diagrams with no text, inference can be essential for comprehension (Butcher, 2006). Kriz and Hegarty's (2007) model of visualization posits that learners engage in both bottom-up and top-down processes when observing visual illustrations. The bottom-up search aids in locating and encoding relevant information, whereas the top-down process immediately plays a role in recognizing features and activating topic knowledge. Such information is then internally represented, then refined by semantic processing to form a more coherent mental model of the illustration. This bottom-up processing relies entirely on a learner's prior experience.

Although diagrams have been demonstrated to facilitate learning, they are not always effective. Larkin and Simon (1987) state that diagrams are only effective over text if the grouped information is presented in such a way that facilitates inference. Despite evidence that diagrams facilitate the construction of mental models (Glenberg & Langston, 1992), they are limited in the types of knowledge that can be directly assessed. Diagrams have been shown to influence measures requiring interpretation and application of knowledge, but not literal or declarative knowledge (Fiore, Cuevas, & Oser, 2003). Diagrams alone have a certain learning value to them, however, this learning effect is potentially increased when combined with descriptive text (Mayer & Anderson, 1991,1992; Mayer, Steinhoff, Bower, & Mars, 1995; Mayer & Gallini, 1990; Mayer, Bove, Bryman, Mars, & Tapangco, 1996).

Researchers have completed years of research into text and diagrams focused to investigating what method of presentation is most effective for learning, and for whom. Text and illustration have been consistently found to facilitate mental model construction (Glenberg & Langston, 1992; Hegarty, Carpenter, & Just, 1990; Levie & Lentz, 1982; Mandl & Levin, 1989; Mayer, 1995; Mayer 1997, Hegarty & Just, 1993), especially when presented concurrently (Mayer & Moreno, 1999; Mayer & Anderson, 1992, 1993). According to the integrated dual-coding hypothesis, contiguous presentation of text and illustrations facilitate the ability to make referential connections between both verbal and visual representations acquired from their respective stimuli to create a coherent understanding (Mayer & Anderson, 1991,1992). Hegarty and Just (1993) found supporting evidence for this, such that learning of mechanical systems was most efficient when combining texts and diagrams on the same page for learners of high prior knowledge as well as spatial ability. Text-diagram combination is advantageous over solely text because diagrams free up working memory resources by serving as an external aid to textual representations. Additionally, text and diagram facilitates learning over solely diagrams because accompanying text helps direct the learner's attention to the relevant corresponding areas on the diagram/s. (Hegarty & Just, 1993). In science learning research, it has almost become an axiom that the ability to learn is dependent on individual differences such as prior knowledge and other cognitive abilities. For that reason, measurement of individual differences are included to accurately predict performance and account for any additional variance not accounted for by treatment manipulations.

Individual Differences in Learning

Prior knowledge. Multimedia learning benefits learners with low prior knowledge the most, rather than high (Mayer, 2009). This comes as no surprise as there has been a large body of research devoted to the role of domain knowledge in acquisition. The majority of research supports the notion that prior knowledge aids learning (Bransford & Johnson, 1972; Bower, Black, & Turner, 1979; Voss, Vesonder, & Spilich, 1980). Prior knowledge moderates the learner's ability to retain the target information given to them. For instance, Spilich, Vesonder, Chiesi, and Voss (1979) explain that high prior knowledge individuals have a more developed knowledge structure, as it contains more concepts and relations than their low knowledge counter parts, which allows them to integrate more information onto an existing structure. One theory that incorporates the relevance of background knowledge is Construction-Integration Theory (Kintsch, 1998). According to Kintsch (1998), a reader forms a surface mental model from the words they read, in turn activating a semantic network that draws from prior knowledge. At this level both appropriate and inappropriate meanings of the words are included. When relatively short textual descriptions are present (1-3 words), shallow processing takes place, but when longer strings of verbal information are present, deeper processing takes place (Kintsch, 1998). In this model, learners with a low level of background knowledge would be at a disadvantage because they would not contain any previous knowledge structure for reference (McNamara & Kintsch, 1996). For that reason, prior knowledge were used here to correlate with learning outcomes and account for variance in learning. Aside from prior existing knowledge as a moderating variable, other individual cognitive factors that are not so easily acquired (albeit non-inherent) may influence a learner's effectiveness in their understanding from text and diagram materials. One such ability is working memory capacity.

Working memory capacity and learning. WMC refers to a one's ability to store and manipulate information from both the short-term and long-term memory store (Baddeley & Hitch, 1974; Conway & Engle 1994). Baddeley broke down working memory into three key subcomponents that are the (1) phonological loop which processes verbal information, the (2) visuo-spatial sketchpad which deals with visual properties, and the (3) central executive which is responsible for coordinating the operations of the two subcomponents and linking them to long-term memory (Baddeley, 1996; Smith & Jonides, 1999). Baddeley (2000) later added the episodic buffer to his working memory model, in which the primary function is to allow temporary storage of multimodal information drawn from both the visuo-spatio sketchpad and the phonological loop, combined with prior knowledge.

Theories have attempted to depict learning processes that occur when learning from multimodal presentations. For instance, Mayer's (2009) Cognitive Theory of Multimedia Learning (CTML) draws from working memory in the sense that processing from a visual and verbal channel occur during multimedia learning. However, this model fails to integrate the usage of the central executive as well as the episodic buffer, which is why investigating the role of working memory in multimedia learning may be worthwhile (Schuler, Scheiter, & Genuchteny, 2011). Schnotz and Bannert (2003) developed a more integrative theory of multimedia learning similar to CTML, called the Cognitive Model of Multi-media Learning (CMML). This model differs from Cognitive Theory of Multimedia Learning in that the conceptual organization is the product of a continuous interaction between four key elements: text surface representation, propositional representation, visual perception/image, and the mental model (Schnotz & Bannert, 2003). Both theories describe the construction of mental models as an interactive process, in which learners must refer to both old and new information, as well as the ability to simultaneously hold verbal and visual representations in working memory to create referential connections (Mayer, 1997). Working memory capacity in both the visuo-spatio sketchpad and phonological loop may dictate how much information can be retained at one time. Thus, WMC may be predictive of the ability create a coherent model from text and illustrations.

WMC has been correlated with reading comprehension as per the reading span test (Daneman & Carpenter, 1980). Students with a higher WMC are able to encode relevant information into memory without extra processing, just as much as students with prior knowledge on the target material (Kaakinen, Hyona, & Keenan, 2003). WMC also has been correlated with science learning (Sanchez & Wiley, 2006), as well as the ability to focus attentional resources (Conway & Engle, 1994). Since WMC is highly indicative of not only reading comprehension (Daneman & Carpenter, 1980), but multimedia learning (Schuler, Scheiter, & Genuchten, 2011), it was incorporated into the present study to test if high WMC learners profit from engaging in self-explaining moreso than low WMC individuals. This hypothesis can be described as an ability-as-enhancer hypothesis where learners' high abilities allow for better performance in a rich environment (Mayer & Sims, 1994; Huk, 2006). The following describes a different cognitive ability that may compensate for an incomplete learning presentation.

Spatial ability. Spatial ability can be defined as the ability to ascertain and preserve an internal representation of a perceived scene in such a way it can be mentally manipulated (Carrol, 1993). An individual's spatial ability may be indicative of how well they retain information from an illustration (Blake, 1977; Hays, 1996; Large, Behesti, Breuleux, & Renaud, 1996, Yang, Andre, & Greenbowe, 2003; Hoffler, 2010; Hoffler & Leutner, 2011). There are plenty of former studies that have attempted to categorize the different types of abilities under the scope of spatial abilities (Hegarty & Waller, 2006; Kozhevnikov & Hegarty, 2001: Zacks, Mires, Tversky, & Hazeltine, 2002). However, SA can be categorized into the following two sub-types of ability: Spatial visualization (SV) and mental rotation (MR) (Carroll, 1993; Cooper, 1975; Cooper & Shepard, 1973; Mumaw, Pellegrino, Kail, & Carter, 1984; Pellegrino & Hunt, 1991). It is worth noting that these two branches of SA are usually highly correlated (Carroll, 1993; Just & Carpenter, 1985; Stumpf & Eliot, 1995). In multimedia learning, spatial visualization influences a learner's ability to visualize movement or sequences of action described by text and diagrams, thus possibly predicting their ability to learn from such forms of presentation (Hoffler & Leutner, 2011).

A study done by Mayer & Sims (1994) showed that learners with high SA benefitted from multimedia presentation more so than low SA learners, stating that high spatial abilities aid in constructing a visual mental model, leaving more cognitive resources available for creating the mental model. Low SA learners tend to create only a representational connection when learning with diagrams and text, as opposed to high SA learners who are able to create referential connections between both mediums (Mayer & Sims, 1994). Another explanation is that high SA permits learners to perform mental animations of images, which serves as a learning advantage over low SA learners (Hegarty, Kriz, & Cate, 2003; Hegarty & Sims, 1994; Cohen & Hegarty, 2007; Huk, 2006). These findings serve as evidence for the proposition that low SA hinders the amount of learning taking place when presented with multimedia presentation that require such mental manipulations. Mayer and Sims (1994) go on to infer that high SA students are able to hold a visual image in visual working memory for a longer period than those with low SA, thus allowing them to incorporate information from the image to its descriptive text (Mayer, 2009). Additionally, spatial ability can play a crucial role when reasoning with diagrams, as higher spatial learners are able to mentally imagine movement depicted in diagrams.

Efficiency in learning from multimedia presentations, mainly text and illustrations, is moderated by individual learner characteristics. Some of those characteristics include a learner's (1) background knowledge on the subject matter, (2) spatial ability, which can facilitate construction of a mental model, and (3) working memory capacity, which is essential for reference making. All three characteristics have the possibility to disadvantage learners, so, how can students of inherently low cognitive abilities or lack of prior experience in a specific domain overcome these challenges to their learning? Multimedia presentations (if done correctly) can help with resolving some of these deficits in individual abilities. However, Chi, Bassok, Lewis, Reimann, and

Glaser (1989) investigated a metacomprehension technique that helps learners create referential connections as well as monitor their learning accuracy (Griffin, Theide, & Wiley, 2009). It is possible that this learning technique aid learners who are disadvantaged in said learning presentations.

Self-explaining Effect

Self-explaining is a strategy that helps the learner retain information and fill in gaps between linking concepts (Chi, Bassok, Lewis, Reimann, & Glaser, 1989). Chi (2000, p. 165) defines the self-explaining effect as "a knowledge-building activity that is generated by and directed to oneself." Self-explaining has been explored in various domains such as biology, physics, or algebra (Chi, De Leeuw, Chiu, & LaVancher, 1994; Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Neuman, Leibowitz & Schwarz 2000), and can be elicited by either humans (Chi, De leeuw, Chiu, & Lavancher, 1994), or computers (Chou & Liang 2009; Aleven & Koedinger, 2002; Housmann & Chi, 2002). Self-explaining has been proposed to have larger effects when learning with illustrations vs. text alone (Roy & Chi, 2005), possibly because the self-explaining requires learners to understand how different structures work together, as opposed to simply learning the names of the structures themselves (Hmelo-Silber & Pfeffer, 2004). Self-explaining has been said to be effective to increase inferences or increasing metacognitive monitoring (Atkinson, Renkl, & Merrill, 2003).

One important distinction was found however, regarding the effectiveness of self-explanation. In high school physics students, metacognitive prompts lead to higher difficulty in problem solving for low ability students (Nokes, Hausmann, VanLehn, &

Gershman, 2011). There are other instances in which self-explanation did not lead to significant learning (Hausmann & Chi, 2002; Kuhn & Katz, 2009; Craig, VanLehn, & Chi, 2007), and the reason for that could be that self-explanation can overload an individual's WMC due to the demand it has on working memory in addition to creating references between visual and verbal representations (De Koning, Tabbers, Rikers, & Paas, 2011).

The majority of research involving self-explaining involves the elicitation of verbal self-explaining. Other studies use computers to record self-explanations (Chiou & Liang, 2009; Hausmann & Chi, 2002). These proved to be efficient methods of self-explaining in the sense that it enhanced knowledge moreso than if no self-explaining took place (Aleven & Koedinger, 2002). There also lies a distinction between content-related (Chi, De Leeuw, Chiu, & LaVancher, 1994; Crippen & Earl, 2007; Hilbert & Renkl, 2009) and content-free (Chou & Liang, 2009) self-explanation prompts, in that content-related prompts allow low ability students to learn better whereas generic prompts allowed for better learning in high ability students (Aleven, Pinkwart, Ashley, & Lynch, 2006). Specific content-related prompts allow learners to become more aware of their level of understanding as they progress through the material (Chou & Liang, 2009). Griffin, Theide, and Wiley (2008) encouraged their learners to self-explain by providing written instructions as well as brief examples of what such explanations may look like, and compared to rereading and read-once conditions. However, students were not required to record their self-explanations in any form, which could have led to the non-significant findings between self-explaining and nonself-explaining groups. In the study, self-explaining was implemented so as to provide deeper level cues for learners to monitor their accuracy because simple rereading may only provide surface-level cues that are not necessarily indicative of learning comprehension.

Interestingly, the manners in which self-explanations are recorded affect the content of the explanations themselves. For instance, verbal (or think-aloud) self-explanations are typically less complete than when written or typed. A possible explanation is that written explanations allow learners to keep record and correct their explanations, in contrast to verbal explanations that are on average more spontaneous and less filtered (Hausmann & Chi, 2002; Chou & Liang, 2009). Despite the format of these explanations, they all share one goal in mind when it comes to learning with problem-solving, or comprehension with text and or diagrams: To allow the learner to self-monitor their comprehension (Griffin, Theide, & Wiley, 2008), and increase their inferential activity (Nokes, Hausmann, VanLehn, & Gershman, 2011), to effectively bridge any gaps that may have been present in the learning material (Chi, De Leeuw, Chiu, & LaVancher, 1994).

When used in conjunction with learning via text or diagrams, students learning with only diagrams produce significantly more self-explanations than students presented with text only (Ainsworth & Loizou 2003). This in part can be explained by the working memory model, which proposes that self-explanations and diagrams would be processed by two separate modalities: the phonological loop (self-explanations) and the visual-spatial sketch pad (diagrams) (Baddeley & Hitch, 1974), in turn allowing for more effective learning (Mayer & Moreno, 2002). In accordance with previous hypothesis (De

Koning, Tabbers, Rikers, & Paas, 2011), it is hypothesized in the present study that participants with low working memory will perform poorly on recall and transfer measures when asked to self-explain, whereas high WMC learners will perform greater in the SE conditions. This follows suit to an ability-as-an-enhancer hypothesis (Huk, 2007; Mayer & Sims, 1994) in such that learners with high WMC will perform better than low WMC learners when cognitive demands are increased due to the nature of self-explaining. The present study aimed to investigate whether or not low spatial ability learners can benefit from multimedia learning (text and diagrams) as much as high ability learners by implementing the learning strategy of self-explaining (Chi, De Leeuw, Chiu, & LaVancher, 1994).

Hypotheses

Diagrams facilitate learning when used properly in a multimedia presentation. However, this learning is dependent on individual difference characteristics such as spatial ability, as well as working memory, and a student's prior experience. Provided that self-explaining has been shown to increase cognitive engagement in learners, allowing them to monitor their learning as well as enhance their ability to create referential connections within concepts, is was expected that implementation of this learning technique may result in resolving deficits attributed to low spatial ability. To test this, the following hypotheses were developed for the present study:

Hypothesis 1. As purported in Mayer and Sims (1994) study, students with low spatial ability have less cognitive resources available to create referential connections between verbal and visual stimuli. Conversely, high SA learners are able to allocate residual cognitive effort to creating these connections. Self-explaining is a strategy that has been shown to facilitate learning by helping to fill gaps that are not explicit in the material. For the present study, it was expected that SA will interact with self-explanation while holding other variables constant in such that learner's with low SA who explain will demonstrate greater learning than high SA students who do not engage in self-explanation. Learning was measured using two recall measures and one transfer measure.

Hypothesis 2. As an ability-as-compensator hypothesis (Mayer & Sims, 1994), SA will interact with the type of presentation in such a way that high SA individuals will perform better on the aforementioned learning measures than low SA learners in non-illustrated conditions. This stems from the argument that high spatial ability learners are able to more efficiently visualize concepts and retain those images in working memory. Once in working memory, referential connections can be made between the imagined visual representation and the explicit verbal representation (Mayer & Sims, 1994).

Hypothesis 3. Although the self-explanation strategy can potentially facilitate learning, it can have a demanding effect on a learner's cognitive resources. Learners with high WMC may have sufficient resources to retain verbal and visual information while constructing inferences between the two via self-explanation (De Koning, Tabbers, Rikers, & Paas, 2011). For that reason WMC is expected to interact with self-explanation while holding other variables constant such that learner's with high WMC will perform better on learning measures in both SE/NSE conditions than low WMC.

Hypothesis 4. The level of a learner's domain knowledge may have an effect on how well they can learn new concepts within the same domain. Prior knowledge provides a structure by which students can reference newly read material with similar information stored in their long-term memory (Kintsch, 1998). Thus inference processing is facilitated by one's prior knowledge (McNamara & Kintsch, 1996). For the present study, prior knowledge is expected to moderate learning in across conditions when holding all other variables constant.

Chapter 2

METHOD

Conditions

The study implements a randomized factorial design with two cognitive measures, and three posttests (later described). The four conditions for the study are designed to investigate the possibility of interactions between self-explaining and individual difference variables, and between individual difference variables and illustrations. Mayer, Bove, Bryman, Mars, & Tapangco (1996) tested learning by manipulating the presentation of a text and set of illustrations regarding the process of lightning systems and found that presenting diagrams with captions to learners was equally as effective as providing them a lengthy passage. However, said study did not measure learners' ability to spatially visualize images in their mind. For that reason the type of presentation was manipulated in such a way that one pair of conditions did not contain accompanying illustrations (NI), and the other pair contiguously contained passage and illustrations (I). In order to see whether or not self-explaining provided a true benefit to low ability learners, one pair of conditions instructed and prompted students to generate self-explanations throughout the presentation (SE), and the other pair only instructed participants to write down any thoughts or ideas that may help them learn the material (NSE, see Appendix G). Instructions for SE conditions were adapted from Chi, De Leeuw, Chiu, and LaVancher (1994) and modified to fit the presentation format of the present experiment (see Appendix H). The result is a 2(SE vs NSE) by 2(I vs NI) factorial design.

Random variables were used to assess the contribution of individual differences to learning outcomes. Said variables include spatial ability, working memory capacity, and prior knowledge. Instead of dichotomizing variables into high and low categories, as the majority of research does, each individual difference variable were analyzed as a continuous variable in regression analysis (described later).

Self-explaining vs. nonself-explaining. The present study recorded self-explanations by way of typing into a computer interface. As in Hilbert & Renkl's (2009) study of self-explaining in concept mapping, no feedback was provided to the participant regarding their explanations for the following reasons: (a) self-explaining with no feedback has been shown to be effective (Schworm & Renkl, 2006, 2007) and (b) not providing feedback is more ecologically valid, since students typically do not have the opportunity to receive feedback from their teacher one-on-one in a classroom with other students.

Students in SE conditions received instructions (as adapted from Chi, De Leeuw, Chiu, & LaVancher, 1994) on how to self-explain prior to reading through the material. One distinction in protocol from the mentioned study is the instructions simply instructed the student how to self-explain, but do not get a chance to practice before the presentation. Self-explaining practice was omitted due to time constraints. Students in SE conditions were prompted to self-explain after each slide by responding to a content-free prompt regarding the material just read. Content-free prompts were implemented as they were previously found to be as effective (but generate less explanations) as content-related prompts in learning measures (Chou & Liang, 2009). Self-explanations were typed into a computer interface provided by Qualtrics online survey platform. Participants in the control, or NSE, conditions were not be prompted to engage in self-explaining or any other specific type of deep-level reasoning, but were still be prompted to record any thoughts or information they felt was useful throughout their reading so as to match the time allocated for SE conditions.

Participants

In order to estimate the amount of subjects that may be necessary to generalize any significant findings, a brief review of the number participants used in similar studies was conducted to approximate an adequate sample size. Studies chosen for review (see Table 1) compared treatment conditions similar to that of the present study and included self-explaining. The average number of participants per cell is 17.85. However, a larger "n" was obtained to provide more power to the statistical analyses.

Recruitment. A total of 200 participants went through the study. Twenty participants were removed because they either (1) did not have a math accuracy score of 85% or better on the AOSPAN, (2) were found to have plagiarized their written response/s, or (3) re-took the study when advised not to. The group sizes were unequal (NSE/I=47, NSE/NI=46, SE/I=51, SE/NI=36). Participants were recruited via Mechanical Turk, a website that provides access to participants in their online subject pool for compensation. As a part of Amazon.com, Mechanical Turk provides researchers the ability to utilize their subject pool which consists of anyone who is proficient enough with a computer to use an internet connection. A possible downfall of this method is that the competency of each participant is undeterminable, however, for that reason a larger number of participants were included in the modification to allow for more statistical power.

Compensation. In order to use Mechanical Turk to run participants, compensation was provided for each person who participated in the study. Considering the amount of time, as well as the ease of access to the study and workload, participants were compensated with $1 USD for their participation. Said amount, although seemingly low upon first sight, is a rather common rate of compensation for participants who complete studies through Mechanical Turk. Funding was provided from the experimenter's personal account and was credited to Amazon.com and distributed to participants through Mechanical Turk.

Statistical Analysis

In order to compare comprehension performance, a 2(SE vs. NSE) by 2(I vs. NI) ANOVA was run within the context of linear regression. Linear regression was used to interpret moderating effects of individual characteristic variables described in sections below. For all regression analyses, the "enter" method was used. In this method, all terms of interest are included in the model to predict each of the learning measures. Within the analyses, t-tests were analyzed for significance and directionality of each predictor term.

Materials

Demographic survey. All participants were required to fill out survey recording demographic information such as their age, gender, how long they have been speaking English, what their current major is, as well as a small set of questions measuring their level of knowledge of weather systems (Mayer, 2009). Minor changes were made to the original demographic survey so as to accommodate for the shift in the way participants may check weather (i.e. participants are asked if they frequently check weather maps online, as well as in the newspaper, as opposed to solely the newspaper).

Learning domain. Participants were asked to read through a body of text that describes how lightning is formed, as well were shown diagrams that correspond to each body of text. The text was taken from Mayer (2000), totaling 577 words, and was divided between five slides. Each body of text per slide had its corresponding diagram visually depicting the content. The diagrams used were reproduced using Microsoft Paint. Conditions that did not contain the illustrations (NI) contain the same text, font size, and position of conditions containing illustrations so as to provide consistency in the manner in which the text is presented in all conditions (see Appendix C for an example of the illustration).

Knowledge retention and transfer. A series of posttest assessments were used to measure the different levels of knowledge for participants. These measures ranged from shallow (i.e. recall) to deeper (transfer) understanding. All posttest learning measures were recorded using Qualtrics website.

True/false. Participants took a 20 question True-or-False posttest about key points of the formation of lightning. Questions were not in chronological order and were derived directly from the text. The 8 concepts core to the understanding of lightning systems were embedded within the 20 questions, while the remaining 12 questions refer to secondary information that is included, but not essential to the understanding of how lightning is formed. (Mayer, Bove, Bryman, Mars, & Tapangco, 1996).

Multiple choice. A multiple choice questionnaire was used to measure retention on concepts. There were fifteen multiple choice questions in total. Six of the questions were derived from Craig, Gohlson, & Driscoll's (2002) study (experiment 1), which categorized the questions according to its salience (explicit vs. implicit) and level of complexity (deep vs. shallow). Additional questions derived from the text were added to the multiple choice test in hopes to assess what type of learning is being facilitated by each condition. The number of questions in each type was as follows: five explicit-deep, explicit-shallow, and implicit-deep questions.

Open answer. An open ended essay response question was administered, asking participants to fully explain their understanding of the material. Additionally, to assess participants' ability to not only understand factual knowledge of how lightning is created, but apply it to solve other problems, they were asked to answer a set of 4 transfer questions, making a total of 5 essay responses (Mayer, 2009).

Paper folding task. To measure participants' spatial abilities, they completed the paper folding task (Ekstrom, French, Harman, & Derman, 1976). In this task participants are to imagine the folding and unfolding of pieces of paper that have a hole punched in them, and correctly select the unfolded piece of paper that demonstrates the hole punched in the correct location as folded piece of paper.

AOSPAN. Participants' WMC were measured using an automated version of the Operation Span task (Turner & Engle, 1989) (AOSPAN) which requires participants to solve basic math problems, concurrently remembering an irrelevant letter presented to them (Unsworth, Heitz, Schrock & Engle, 2005).

Procedure

Experiment sessions were conducted in a remote environment dictated by the participant. The only requirements were a technologically compliant computer (audio-capable. up-to-date browser, working internet connection). Participants were advised to select a distraction-free setting due to the nature of the study. Due to the remote environment, a maximum time limit was given to complete each segment, but participants were free to advance at their own pace.

Participants were given five minutes to read the information letter to become familiarized with the general goal of the study. Five minutes were given to complete the initial demographic survey and pretest, after which they were given five minutes to read and complete part 1 paper folding task. Next, they viewed a PowerPoint presentation of the target material to read and were given instructions on completing the reading. Participants in all conditions were given 13 minutes to complete their task. The timing allotted for viewing each slide was calculated using the number of words per slide. In order to allow participants within a range of reading speed ability to read through all the content, a slower reading rate than the national average (250 words per minute) was used of 200 words per minute. Time allotted for participants to engage in self-explanations, unlike time allotted to reading the text, is not proportionate to the amount of text or number of concepts per slide. Instead, two minutes is given for participants to either self-explain, or write down anything they deem helpful to their understanding depending on their condition. The timing for each textual slide can be found in table 2.

Participants in the NSE conditions were allotted the same amount of time as the SE condition (13 minutes) go through the presentation. However, instead of being prompted to self-explain, they were simply prompted to write down anything that might help them remember the material they read. Upon completion of the material, participants were given twenty-five minutes to complete the true/false, multiple choice, and essay response posttests. Next, they completed part 2 of the paper folding task, taking approximately five minutes. The AOSPAN task was then administered, which took no longer than 25 minutes. Following the AOSPAN task, Participants were then debriefed and given the opportunity to ask any questions they may have regarding the study before exiting. The entire experimental session had a duration of approximately one hour and twenty-eight minutes.

Data Analysis

In order to test the hypotheses, multiple regression analyses were conducted on the predictors and dependent variables (described later) used to form the hypotheses. Significance values of models with each learning measure were observed to assess how well the model predicted behavior. β values for each predictor were reported to assess whether or not a predictor accounted for a significant amount of variance on an individual basis.

Predictor variables. As suggested by Cohen, Cohen, West and Aiken (2002), the term for spatial ability (SA) was centered to create a new variable with a meaningful zero, since there were no participants who scored less than 1 on the pre-test for SA. In order to view the predictability of the self-explaining conditions, a new variable was created coding the NSE (coded 1, weighted .5) and SE (coded 2, weighted -.5) condition. To test the interaction between spatial ability and self-explanation in the first hypothesis, the product of the SE contrast codes with the continuous variable SA was used.

Dependent variables. An open ended question developed by Mayer (2009) was used to assess recall of facts from the learning material. Three dependent variables were used as measures of transfer learning. The first consisted of four open ended questions previously developed by Mayer (2009), of which a unitary construct was created using the sum of the questions. The second transfer measure utilizes only five of the multiple-choice questions, which are designed to assess implicit-deep knowledge. The third is the sum of explicit-deep and implicit-deep questions, totaling ten questions. The implicit-deep and explicit-deep questions were isolated and considered a separate source of transfer knowledge (see table 3). This is because learners were required to infer the answer from material that was not expressed explicitly, forcing them to think constructively to respond (Chi, 2009).

Transfer Question Scoring. For Mayer's (2009) lighting formation material, the coding scheme from Mayer and Moreno (1999) was used. In this coding scheme, 19 points of information from the text are used to assess understanding. Examples from the coding scheme were used as reference to grade open ended transfer responses. However, if the participant provided a response that was not in Mayer and Moreno's grading scheme, but still addressed the question in an accurate manner according to the learning material, a point was still awarded. In order to reduce bias in scoring responses, two experimenters scored each of the open-answer questions. Scoring was then reconciled between both experimenters on each question so that each score was mutually agreed upon.

Chapter 3

RESULTS

H1: Spatial ability moderates learning across self-explaining.

To test the hypothesis that self-explanation compensates for learning deficiencies brought on by a lack of spatial ability, a hierarchical multiple regression analysis was conducted. In each equation, individual difference variables (multiple choice pretest and spatial ability) were entered as the first block. The second block contained the contrast codes for SE conditions. Finally, the third block entered in the interaction term for SE-SA. β for individual predictors were assessed for significance. A correlation matrix showed there to be a strong correlation between the multiple choice pretest and SA. WMC did not correlate significantly with the multiple choice pretest (See table 4)

Results of the regression analysis provided no supporting evidence for the first hypothesis. Using open-ended transfer questions as the criterion, F tests within the linear regression yielded nonsignificant results for each of the three blocks, including individual difference variables (F(2,175)=1.145, p=.321), SE conditions (F(3,175)=.880, p=.453), and the SA*SE interaction term (β =.080, t(175)=1.068, p=.287; F(4,175)=.945, p=.439). With the implicit-deep questions as the criterion, each block was found to account for a significant amount of variance (See table 5). However, the additional variance accounted for by the entering of the third block containing the SE*SA term was nonsignificant (F(4,175)=.029, p=.866). When predicting performance on all deep questions, each hierarchical model was found significant (p<.001), which may have been primarily attributed to significant terms SA (β=.276; t(175)=4.176, p<.001) and multiple choice pretest (β=.386; t(175)=5.818, p<.001). The other terms for SE (β=-.060; t(175)=-.94, p=.348) and SE*SA (β=-.027; t(175)=-.416, p=.678) were nonsignificant as well. Findings suggest that high spatial ability learners do not significantly benefit from self-explaining more so than their low spatial ability counter parts. See full details in tables 5-8.

H2: Spatial ability interacts with illustration.

The second hypothesis assumed that knowledge assessments will reflect an interaction a learner's SA and whether or not they were exposed to a visual illustration while learning.

H2 Dependent variables. The aforementioned lists of dependent variables were used as dependent variables in multiple regression analyses with the addition of a new variable that contained the control condition no-illustration (coded 1, weighted .5), and the treatment condition illustration (coded 2, weighted -.5). To test the interaction term for the second hypothesis, the variable containing codes for the illustration condition (labeled PIC) was multiplied by SA. The term SA was included in the equation due to its inclusion in the higher order term, as suggested by Aiken, Cohen, Cohen, and West (2002).

Hierarchical regression for the second hypothesis was run in the same manner, that is, a model was tested for each of the learning measures using the previously mentioned predictors. The interaction hypothesized was not significant for any of the learning measures. The closest metric to which significance was approached for the interactions term was retention (β= -.303, t(175)=-1.71, p=.089). All other significance values for learning measures were above p=.400. Significance at the $p<.001$ level were obtained for models with the following criteria: multiple choice ($F(4,175)=27.36$), total deep ($F(4,175)=17.3$), implicit-deep ($F(4,175)=14.05$), explicit-deep, and true/false questions ($F(4,175)=18.1$). Spatial ability significantly predicted performance in the multiple choice ($\beta=.353$; $t(175)=5.73$, $p<.001$), total deep($\beta=.273$; $t(175)=4.10$, $p<.001$), implicit-deep ($\beta=.236$; $t(175)=3.46$, $p=.001$), explicit-deep ($\beta=.234$; $t(175)=3.31$, $p=.001$), and true/false measures ($\beta=.280$; $t(175)=4.24$, $p<.001$). SA accounted for marginally significant amount of variance in the retention measure ($\beta=.146$; $t(175)=1.92$, $p=.06$). Illustration conditions only predicted significance for the retention measure ($\beta=.419$; $t(175)=2.37$, $p=.02$), and approached significance for the true/false measure ($\beta=-.266$; $t(175)=-1.73$, $p=.09$). The β value of -1.391 of the illustration variable suggests that learners who did not view diagrams nearly performed significantly better than learner in the opposite condition. For a complete display of hierarchical regression statistics for the four major dependent measures, see tables 9-12.

H3: WMC interacts with self-explaining.

Hypothesis three maintained that a learner's working memory capacity were indicative of the effectiveness of self-explaining. Due to the taxing nature of the act of self-explaining on cognitive resources, it is hypothesized that learners with a low working memory capacity will fail to maintain the learning material within their working memory as efficiently as their high-capacity counterparts, thus affecting the amount of knowledge that can be successfully acquired.

H3 Dependent variables. Participants' scores for their working memory measure as defined by Unsworth, Heitz, Schrock, and Engle (2005) were used as the predictive term in the multiple regression analyses for the first set of analyses for the third hypothesis. The same regression analyses were run a second time using the total correct letters obtained in the AOSPAN as the predictor, instead of the traditional OSPAN score which only adds the number of correct letters recalled in a set completed with no mathematical errors. In similar fashion to previous hypotheses, an interaction term was created for each analysis by multiplying either the traditional OSPAN score or total.

No significant interaction between SE and WMC was found for any of the learning measures of the dependent variable. However, WMC alone was found to be a significant predictor of the implicit-deep questions (β=-.136; t(175)=-2.02, p=.045). The results suggest that working memory capacity may not in this instance be widely predictive of the learning performance, nor does it interact with the self-explaining conditions on explicit-deep (β=-.116; t(175)=-.56, p=.578), implicit-deep (β=.025; t(175)=.127, p=.899), deep total (β=-.058; t(175)=-.297, p=.767), and open-ended (β=-.134; t(175)=-.607, p=.544) transfer questions (see Tables 13-16).

To further investigate the third hypothesis, the same regression analyses were conducted using the total number of correctly recalled letters as the predictor for working memory capacity. There was still no significant interaction found when using the total correct letters recalled as a measure of WMC. On its own, WMC was a significant predictor for only one learning measure: true/false questionnaire (β=.145; $t(175)$=2.09, p=.038) (see Tables 17-20).

H4: Prior knowledge predicts learning.

The fourth hypothesis states that prior knowledge is indicative of learning. For these analyses all dependent variable learning measures were predicted from the multiple choice pretest. The multiple choice pretest was used over Mayer's meteorology study on account of two reasons. Firstly, since there are a higher number of items on the multiple choice test, it allows for wider sampling across the pretest measure. This means that it were a more accurate representation of the differences between groups in terms of performance, due to higher range (multiple-choice: M=6.13, SD=2.355; meteorology pretest: M=5.39, SD=2.797). Secondly, the multiple-choice test measures specific knowledge regarding lightning systems, whereas Mayer's (2009) meteorology test is based upon self-report which may be unreliable. Much in agreement with what was predicted, prior knowledge as measured by the multiple choice pretest was a significant predictor of learning performance (p<.001) in all but the following two measures: Transfer (β=.074; $t(175)$=.986, p=.325) and retention (β=.014; $t(175)$=.19, p=.851). See table 21 for hypothesis 4 statistical analyses.

Chapter 4

DISCUSSION

The aim of the current study was to investigate the effectiveness of self-explaining when learning from diagrams and text, especially within students of differing cognitive abilities, mainly spatial ability. Results of the transfer knowledge performance did not support the major hypotheses with respect to individual differences and their effect on learning abilities. Only one of the four hypotheses was supported.

Spatial Ability and Self-explaining

The first hypothesis held that the act of self-explaining would allow for learners with low spatial ability to verbalize their task, facilitating referencing between text and diagrams. By verbalizing the task, instead of attempting to visualize it, they may have more familiarity with that sort of information integration, thus facilitating bridging the information presented from both mediums. Participants with higher spatial ability were expected to efficiently mentally animate the movements depicted in the text and diagrams to better understand the process being described. Analysis of learning performance showed there to be no significant interaction between self-explaining and spatial ability. Scores from students who did or did not engage in self-explaining were not moderated by their spatial ability, resulting in no supportive evidence for the first hypothesis.

The findings for this hypothesis show there to be no indication of learning compensation for low spatial ability learners who self-explain. However, Kastens and Libens (2007) devised a study in which a task requiring spatial visualization was completed by students who either self-explained or not. In this study, students were to physically explore a school campus, searching for colored flags in various locations. Once flags were found, they were asked to place a respectfully colored sticker on a topographical map corresponding to its location. Students who explained their location placed their stickers significantly more accurately on the map than the baseline condition. Kastens and Liben held that participants who explained their reasoning for their note placement were more aware of fallacies in their answers, allowing them to adjust their placement to a more accurate map location. This meta-cognition is a common effect of self-explaining (Chi, De Leeuw, Chiu, & LaVancher, 1994), and the reason it was hypothesized to help students be aware of their deficiencies in visualization of the lightning process.

One distinct difference between this and the present study's design is the nature of the spatial visualization task. The present study asks the learner to visualize movement depicted in a static diagram. Kastens and Libens asked their participants to manipulate their exposure to the surroundings to match that of a topographical map. Mayer and Sims (1994) conducted an experiment much closer to that of the present study. In their study, participants were asked to learn about either a tire pump or circulatory system. Animations were either presented with auditory narrative (contiguous) or successfully one after the other. Learners with low spatial ability scored significantly less on learning measures when exposed to both visual and auditory material. Mayer and Sims demonstrated evidence that learners with low spatial ability allocate all of their cognitive resources to creating representational connections, rather than referential. Referential connections are what allow for integration and efficient comprehension of material. It is specifically this deficit expressed in Mayer and Sims study that the present study hoped to resolve through self-explaining. However, results of the present study did not replicate, nor show a compensatory ability in students who self-explain (for further elaboration, read section *limitations and future improvements*).

The findings in relation to self-explanation are inconsistent with the majority of previous research. Participants in self-explaining conditions should have performed better in post learning performance as demonstrated previously (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Chi, De Leeuw, Chiu, & LaVancher, 1994; Kastens & Libens, 2002; Koning, Tabbers, Rikens, & Paas, 2011; Berthold, Eysink, & Renkl, 2009). Instead, no significant learning differences were found, which is consistent with Hausmann and Chi's (2002) study in which self-explanations were elicited via computer interface. Other studies also were not able to replicate a self-explaining effect. Nokes, Hausmann, VanLehn, and Gershman (2011) investigated further the role of prior knowledge with the types of self-explanation prompts. More in specific, learners with low prior knowledge will not benefit from prompts that are intended to help them revise their current mental model. This can be used to explain null findings across SE conditions in the present study because mental model-revising prompts were utilized. It is possible that the act of typing may have cognitively overloaded learners in SE conditions as well (Hausmann & Chi, 2002).; Kuhn and Katz (2009) found that students engaging in a scientific inquiry task while self-explaining showed less causal inference performance on a transfer task than the non-self-explaining condition. However, the task in the study does not parallel the present study's task, as it involved data reading. Craig, VanLehn, and Chi (2008) contrasted self-explanations with deep-level reasoning questions between groups and found no significant differences between groups. However, the goal of the study was to test how well deep-level reasoning questions generalize to the classroom environment, whereas the current study sought to investigate the compensatory effectiveness of self-explanations in a remote learning environment.

Spatial ability and illustrations

Other differences in individual cognitive capacities were taken into consideration for additional predictions. The second hypothesis posits that participant's spatial ability would impact learning by facilitating participant's ability to integrate the study's material, depending on how it was presented. It was predicted that participants with higher spatial ability would have more residual cognitive resources. These resources in turn can be used to bridge inferences between these mental animations, the material they read, and their prior knowledge. In comparison, learners with low spatial ability will have had minimal residual cognitive resources to allocate to integrative learning.

Spatial ability demonstrated to be a strong predictor for most of the outcomes of the present study. When it comes to learning with verbal and visual stimuli, spatial ability has been shown predict learning outcomes when the domain involves understanding and mentally manipulating movements (Mayer & Sims, 1994, Yang, Andrew, & Greenbowe, 2003. In Münzer, Seufert, and Brünken's study (2009), students' spatial ability was measured before learning about molecular structure and process of ATP. The study presented the material to students either via animations, enriched static pictures, or simple static pictures. Spatial ability was shown to predict performance in the enriched static pictures, meaning that students with high spatial ability performed better than those with low SA. This was not true for the simple static picture condition, and was attributed to the overall difficulty faced by learners having to visualize movement that was not cued. For the present study, no significant interaction between spatial ability and illustration conditions were found. This may be supported by Münzer, Seufert, and Brünken's findings positing that perhaps the materials depicted movements that were equally challenging of spatial ability. This serves as a possible explanation for not having found an interaction between spatial ability and illustration conditions.

Working memory capacity and self-explaining

High WMC learners were expected to perform better in self-explaining conditions than low WMC participants. This is according to the capacity approach in which the capacity for working memory is linked directly to the outcome. In this approach, WMC could predict variance in learning outcomes (Andrade, 2001). However, working memory capacity was not demonstrated to interact with self-explaining conditions. This is inconsistent with De Koning, Tabbers, Rikens, and Paas' study (2011). In the study, participants either self-explained or not, while viewing animations that were either cued or uncued. Participants who self-explained in the cued condition outperformed those in the uncued condition. De Koning and colleagues posit that this might be due to the taxing nature of self-explaining on working memory capacity. This was deduced on the notion that cuing reduces working memory load by focusing attention on relevant areas and reducing attention on distractors, allowing for those resources to be allocated to self-explaining.

Participants' working memory capacity was measured using two metrics (traditional OSPAN score and total correctly recalled letters) in expectation that it would significantly predict learning performance. Akin to the results of the first hypothesis, working memory capacity did not significantly interact with the self-explaining condition. This initial hypothesis spawned from previous claims that self-explaining may tax working memory, thus unearthing individual differences in performance (De Koning, Tabbers, Rikers, & Paas, 2011). However, traditional OSPAN scores on its own did predict learning performance in one transfer learning measure (implicit-deep questions). Oddly, total correctly recalled letters was found to significantly predict learning in the true/false questionnaire. Said results were not in support if this third hypothesis.

Prior knowledge and learning

Lastly, prior knowledge was to be a significant indicator of performance on learning measures. This is in agreement with previous findings that prior knowledge allows for the newly acquired material to integrate with previous knowledge in meaningful and effective ways (Ainsworth & Burcham, 2007; Chi, 2000; Chi, De Leeuw, Chiu, & LaVancher, 1994; Chiesi, Spilich, & Voss, 1979; Cote, Goldman, & Saul, 1998; Wolfe & Goldman, 2005; Yekovich, Walker, Ogle, & Thompson, 1990; McNamara, 2001; McNamara, Kitsch, Songer, & Walter, 1996; McNamara & Kintsch; 1996). All multiple-choice scores (deep total, explicit-deep, implicit-deep, true/false), as well as true/false were significantly predicted by the multiple-choice pretest. The pretest, however, did not predict performance on Mayer's transfer or retention questions. This may be attributed to the fact that these questions have a different format (open ended vs. multiple-choice).

Limitations and future improvements

The current study has several limitations that could have impacted the observed results. To begin, it is possible that the learning material did not tax the learner's working memory sufficiently to see any effects on their performance. According to Baddeley (2000) the visuo-spatio sketchpad and phonological loop are the subcomponents in which visual and auditory (respectively) information are stored and manipulated. It is here in which capacity differences will overload the subcomponents if the learning presentation contains a large amount of information. However, if the learning material does not require a significant amount of processing by the visuo-spatio sketchpad nor phonological loop, learners of all levels of WMC were able to efficiently process the information. This will result in no differences in learning outcomes, as was witnessed in the present study.

Additionally, a material that has been shown to test learners' spatial ability may be more appropriate for testing this hypothesis. Lightning systems material was adopted for the present study in hopes that the movements described in the text and images would require participants to visualize those movements. However, imagining moving parts may be a task more suited for learning material on mechanics, as previously demonstrated in other studies (Hegarty, 1993; Mayer & Sims, 1994). Also, all materials used should be empirically tested so as to ensure their validity. The present study contained one validated learning measure from Mayer (2009) measuring transfer and superficial knowledge.

However, one measure (true/false), and half of the multiple choice test in the present study were created by the author.

Secondly, the manner in which self-explanations were elicited could have influenced how successful it was implemented. That is, whether or not self-explanations were effective. Due to the methodology, it is uncertain as to whether or not the participants truly engaged in self-explaining. Participants who merely regurgitated material (or nothing at all) versus participants who actively engaged in self-explanations may not have sufficiently interacted with the material for information integration to occur (Chi et al., 1989). In addition, self-explaining was elicited in an open ended manner using generic prompts with no scaffolding. Self-explanations have been shown to be most effective when scaffolding occurs (Berthold, Eysink, & Renkl, 2009). Another influential factor in the effectiveness of self-explaining lies in how specific the prompts are. With respect to prior knowledge, students with less knowledge require content specific prompts for better learning, whereas high knowledge learners benefit from generic prompts (Aleven, Pinkwart, Ashley, & Lynch, 2006). The current study contained generic prompts (see Appendix B) as opposed to content-specific prompts. In a future study, content specific prompts may be more appropriate as the domain is a relatively unknown subject as demonstrated through prior knowledge assessment. Additionally, a review of literature conducted by Wylie and Chi (in press) revealed that specific prompts are most beneficial when learning via multimedia presentations. This may be attributable to the multiple resources in such presentations that require active integration for maximum benefit (Moreno & Mayer, 2007).

The environmental conditions in which participants completed the study were dictated by the participant. All that was needed to participate was a computer with internet connection and working speakers. Participants were told to complete the study in an isolated environment to avoid outside interruptions that may steal their attention. According to Mason and Suri (2012), the lack of attention of MTurk “workers” may compromise their participation data. Despite the efforts to facilitate valid self-explanations, there is ultimately no control over participants’ final actions, as well as environment.

Whether or not self-explaining is efficient in various settings has been a question of recent investigation. Earlier studies facilitated self-explanation in a laboratory setting (Chi, De Leeuw, Chiu, & LaVancher, 1994; Renkl, Stark, Gruber, & Mantl, 1998), Additional studies have implemented the self-explaining technique in a classroom setting (Craig, VanLehn, & Chi, 2008, Aleven & Koedinger, 2002; McNamara, Levinstein, & Boonthum, 2004; Nokes-Malach, VanLehn, Belenky, Lichtenstein, & Cox, 2012). The current study introduces a semi-new setting in which the self-explaining effect is being studied. In Aleven and Koedinger’s (2002) study, students were prompted to self-explain using a cognitive tutoring system that provided scaffolding. Although participants completed the study using a computer-based system, its implications were for a classroom setting. The present study elicited self-explanations via a computer in a setting chosen by the participant, and could have ranged from any series of locations. The setting for participants was not recorded for the present study, but may provide further insight as to what settings, if any, self-explanations are generalizable to.

Scrutiny of the self-explanations themselves may allow for more distinguishable results. A recommendation for further analysis would be to analyze the content of participants' self-explanations to create a variable that captures whether or not participants truly self-explained (Ainsworth & Burcham, 2007; Koning, Tabbers, Rikens, & Paas, 2011). Doing so will allow for a much cleaner and irrefutable distinction between self-explainers and nonself-explainers in statistical analyses. However, according to Hausmann and VanLehn (2007), effectiveness of self-explanations is attributed to the *activity* of generating explanations, rather than the content of the explanations themselves. Under this prediction, any effects of self-explanations should have been salient in the present study due to the fact that participants provided self-explanations when prompted. Should the present study hold, it will have provided results contrary to that of the claims made by Hausmann and VanLehn.

Future directions

The effectiveness of self-explaining in learning spatial ability-taxing material can be further investigated. Such a study could yield actionable results in terms of implementing learning strategies for various students in fields that require high spatial ability. Additionally, the question as to whether or not self-explanations can successfully be implemented, that is to say, can have an effect in a remote online learning environment still needs further investigation. Future studies can expand on the way self-explanations are prompted in such a setting to fathom which method allows for participants to fully engage in the explanations so as to facilitate learning.

Conclusion

The present study sought to improve deficits within learners with low spatial ability, by implementing a self-explanation technique. The prediction was that verbalization of a spatial task would allow learners with low spatial ability to form more complete mental models. However, working memory did not moderate learning performance across self-explaining conditions as predicted. Similarly, spatial ability did not interact with illustrations conditions. The only significant prediction made was that prior knowledge would predict learning outcome.

More specifically, Mayer's (2009) lightning systems materials have widely been implemented within controlled lab settings. But, the present study showed no significant findings for the hypotheses. Despite the lack of significant findings, this introduces the possibility of the learning materials, if not the effect itself, not faring well outside a controlled environment. However, the current study failed to replicate these findings in a broader online sample of the population. This brings into question the generalizability of the original findings and points toward the need for more investigation within a real-world learning environment. This may be of interest to science learning researchers who hope to gain insights as to how to improve learning in a remote setting chosen by the participant, which is often the learning environment for the home-schooled and online learning environments.

The present study demonstrated a lack of evidence for self-explaining compensating for low spatial ability in a spatial visualization learning task. This may indicate that verbalization of a spatial task is not adequate for better learning of spatial ability taxing subjects. This means that learners disadvantaged for their low spatial ability may need to find other ways in which they can improve comprehension of domains requiring that ability. Since students with low spatial ability are inherently disadvantaged when learning concepts requiring mental manipulations, learning techniques that may aid in compensating for this low ability become prevalent. Such fields include the science, technology, engineering, and mechanics, which all require a certain degree of understanding of spatial visualizations and mental rotation. The present study attempted to further investigate the role of self-explanation in multimedia learning as moderated by individual differences. Further studies should continue to examine multimedia learning in a more realistic world environment so as to decipher how learning can be facilitated. E-learning environment provide remote means for instruction that is influenced by individual differences. Of these individual differences, evidence has been found indicating that spatial ability affects how well visual information is integrated. Similarly, differences in working memory capacity have been shown to moderate learning. Further research is required to investigate how deficits in either of these abilities can be compensated for in remote learning environment.

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APPENDIX A

TRUE/FALSE QUESTIONNAIRE

1. Lightning is defined as the discharge of electricity resulting from a large amount of positive charges between the cloud and the ground. F – It results from the difference in electrical charge (i.e. negative vs. positive).
2. Clouds are formed by water vapor condensed into water droplets. T2
3. Water in the bottom portion of the cloud is suspended by updrafts F – Top portion
4. Clouds are formed by cold winds above freezing level. F1 – Are formed by warm updrafts.
5. Falling water droplets and crystals cause upward drafts into the cloud F4 – Downward drafts are caused by falling droplets and crystals.
6. Water droplets and ice crystals fall from the cloud. T3
7. Charges begin to build as a result of the moving air within a cloud T5
8. Negatively charged particles rise to the top of the cloud, as positively charged particles fall to the bottom of the cloud F5 – Negative particles fall to the bottom of the cloud. Positive to the top.
9. Stepped leaders move downward in a straight path towards the ground F – Move downward in steps…
10. When downdrafts reach the ground, they spread out in various directions, producing gusts of warm wind people feel just before the start of rain. F – Cold wind is produced.
11. As the stepped leader nears the ground, positively charged upward-moving leaders from ground objects travel up to meet the negative charges. T
12. The upward moving leader from the tallest object is usually the first to meet the stepped leader to complete a path between the cloud and earth. T6
13. The two leaders generally meet no more than 50 feet above the ground. F – Typically meet at 150ft above ground.
14. Once the leaders meet, negatively charged particles then rush from the cloud down its path to the ground. T7
15. An opposite charge is induced by the leader stroke as it nears the ground. T8
16. The upward travel of opposite charges is the direct cause of the thunder heard after lightning. F – Thunder is caused by the expanding of air caused by intense heat.
17. In very rare cases, dart leaders carry more negative charges down the main path, resulting in further flashes of lightning. F – It is very common
18. Rising and falling air currents within the cloud may cause hailstones to form. T
19. Paths created by stepped leaders usually have many branches. T
20. The upward motion of charges is the return, and it reaches the cloud in about 70 milliseconds. T

APPENDIX B

PROMPTS AND OPEN ANSWER QUESTIONS

Self-explanation prompt

Take a moment to write down you self-explanations on what you have just read considering the following: What new information does each slide provide for you, how does it relate to what you have already read, does it give you a new insight into your understanding of how lighting is formed, or does it raise a question in your mind.

Control condition prompt

Take a moment to write down any notes or thoughts on what you have just read.

The slide will automatically advance after time is up.

Retention question

1. Please write down an explanation of how lightning works.

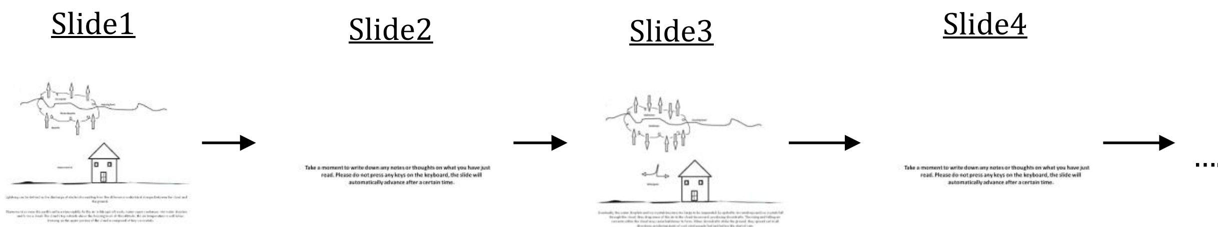
Transfer questions

1. What could you do to decrease the intensity of lightning?
2. Suppose you see clouds in the sky but no lightning. Why not?
3. What does air temperature have to do with lightning?
4. What causes lightning?

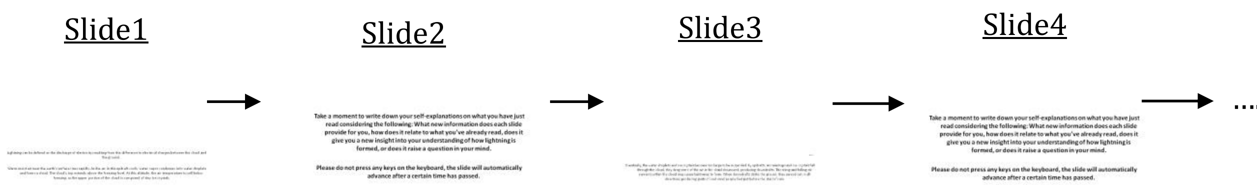
APPENDIX C

SAMPLE OF CONDITIONS

NSE/I condition



SE/NI condition



APPENDIX D

DEMOGRAPHIC QUESTIONNAIRE/PRIOR KNOWLEDGE ASSESSMENT

PIN#:________

Demographics

1. Age:_______
2. Gender:________
3. Native English Speaker? Yes No
4. What is your major? __________________________
5. Please place a check mark next to the items that apply to you:

    ____I regularly read the weather maps online/in a newspaper.

    ____I know what a cold front is.

    ____I can distinguish between cumulous and nimbus clouds

    ____I know what low pressure is.

    ____I can explain what makes wind blow

    ____I know what this symbol means: 

    ____I know what this symbol means: 

6. Please put a check mark indicating your knowledge of meteorology

    _____ Very much

    ____

    ____ Average

    ____

    ____Very little

APPENDIX E

MULTIPLE CHOICE QUESTIONS (FORM A)

1. What causes a flash of lightning?
   a. The return stroke*
   b. Negatively charged leader
   c. Positively charged leader
   d. Negative charges rushing from the cloud

2. When do downdrafts occur?
   a. When air is dragged down by rain*
   b. When air currents cool and fall back to earth
   c. When cold air hits the ground
   d. When there are unbalanced electrical charges between the ground and the clouds

3. What happens as the stepped leader from the cloud nears the ground?
   a. Lightning immediately follows its path
   b. Extreme heat causes the air to expand, producing the sound of thunder
   c. Dart leaders branch out from the initial stepped leader, carrying negative charges
   d. Positively charged leaders from the ground rush upwards to meet the stepped leader*

4. What is the function of dart leaders?
   a. Carry additional negative charges down the path of the stepped leader*
   b. Branch out different paths from the stepped leader to meet new upward leaders
   c. Travel upwards to connect to downward stepped leaders
   d. Extend the stepped leader to make contact with lower objects at ground level

5. Process of forming a cloud occurs when:
   a. Warm moist air rises and the air cools, causing condensation into water droplets that form a cloud*
   b. Cool air rises over and the air becomes heated, causing condensation into water droplets that form a cloud
   c. Cool air descends from above freezing level and condensates, forming a cloud
   d. Warm air descends from above freezing level and condensates, forming a cloud

Explicit—shallow

6. The upper portion of the cloud is made up of what?
   a. Water droplets
   b. Cold air
   c. Ice crystals*

d. Water vapor

7. What part of the cloud are the negatively charged particles located in?
    a. Bottom part
    b. Center of the cloud
    c. Outside edge
    d. Top part*

8. What is a stepped leader?
    a. The upward path by which positively charged particles travel
    b. The upward path by which negatively charged particles travel
    c. The downward path by which negatively charged particles travel
    d. The downward path by which positively charged particles travel

9. What is a return stroke?
    a. The upward path by which positively charged particles travel
    b. The upward path by which negatively charged particles travel
    c. The downward path by which negatively charged particles travel
    d. The downward path by which positively charged particles travel

10. Clouds are formed by what?
    a. The rising of warm, moist air
    b. Water vapor that condenses*
    c. As a result of cold down drafts and rising updrafts in the air
    d. As a result of cold drafts occurring above freezing level

Implicit—deep

11. Why does lightning strike buildings and trees?
    a. They are higher than the ground
    b. A build-up of positive charges
    c. It is the point where the negative leader ends
    d. Positive leader starts at these points*

12. Why does it get colder right before it rains?
    a. Positive charges are absorbed into the clouds
    b. Warm moist air rushes upward into the clouds
    c. Cold downdrafts of air fall from*
    d. Warm surface air rapidly cools

13. What increases the length of time to which you see the series of flashes or lightning?
    a. Additional strokes of lightning caused by dart leaders*
    b. Additional negatively charged particles rushing down the stepped leader
    c. Additional positively charged particles rushing up the upward leader
    d. Additional upward leaders meeting the stepped leader

14. What is the difference between the flash of a leader stroke and a return stroke?
    a. The return flash is brighter than that of the leader stroke*
    b. The flash of the leader stroke is charged primarily of negative particles
    c. The flash of the return stroke is charged primarily of negative particles
    d. The flash of the leader stroke is charged primarily of positive particles

15. Why does warm air rise from the earth's surface?
    a. The air is pulled by upward drafts
    b. The lack of density in hot air causes it to rise*
    c. The cold air attracts the warm air, causing it to rise
    d. Positively charged particles in the hot air are attracted to positively charged particles in the cold air above

---

*Correct Response

APPENDIX F

PAPER FOLDING TEST

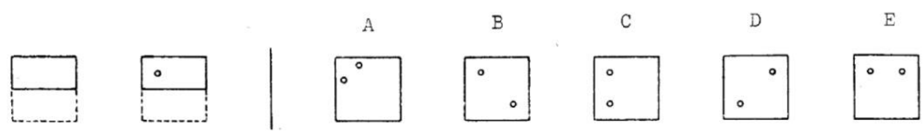
68

Name / ID: ________________________________

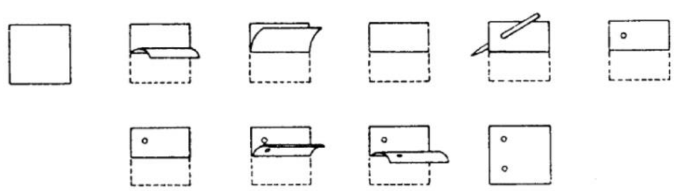
Paper Folding Test – VZ-2

In this test you are to imagine the folding and unfolding of pieces of paper. In each problem in the test there are some figures drawn at the left of a vertical line and there are others drawn at the right of the line. The figures at the represent a square piece of paper being folded, and the last of these figures has one or two small circles drawn on it to show where the paper has been punched. Each hole is punched through all the thicknesses of paper at that point. One of the five figures at the right of the vertical line shows where the holes will be when the paper is completely unfolded. You are to decide which one of these figures is correct and draw an X through that figure.

Now try the sample problem below.
(In this problem only one hole was punched in the folded paper.)



The correct answer to the sample problem above is C and so it should have been marked with an X. The figures below show how the paper was folded and why C is the correct answer.



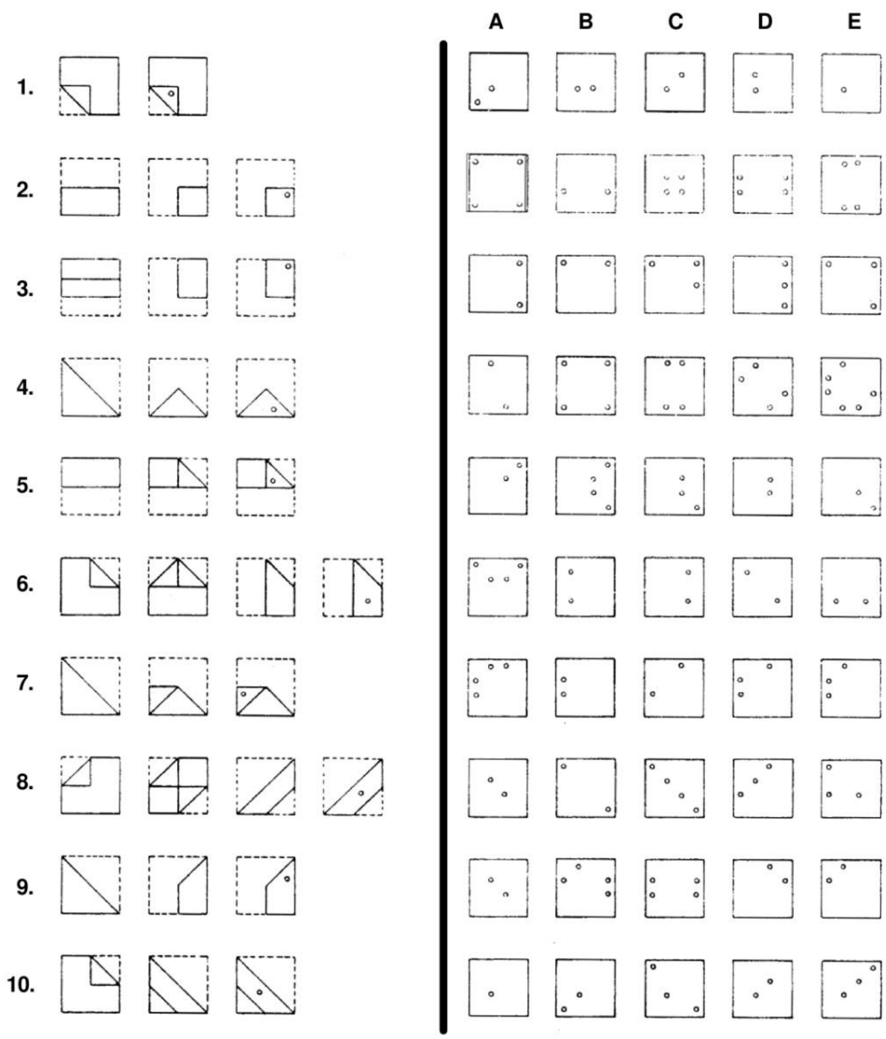
In these problems all of the folds that are made are shown in the figures at the left of the line, and the paper is not turned or moved in any way except to make the folds shown in the figures. Remember, the correct answer is the figure that shows the positions of the holes when the paper is completely unfolded.

Your score on this test will be the number marked correctly minus a fraction of the number marked incorrectly. Therefore, it will <u>not</u> be to your advantage to guess unless you are able to eliminate one or more of the answer choices as wrong.

You will have <u>3 minutes</u> for each of the two parts of this test. Each part has 1 page. When you have finished Part 1, <u>STOP</u>. Please do not go on to Part 2 until you are asked to do so.

DO NOT TURN THIS PAGE UNTIL ASKED TO DO SO.

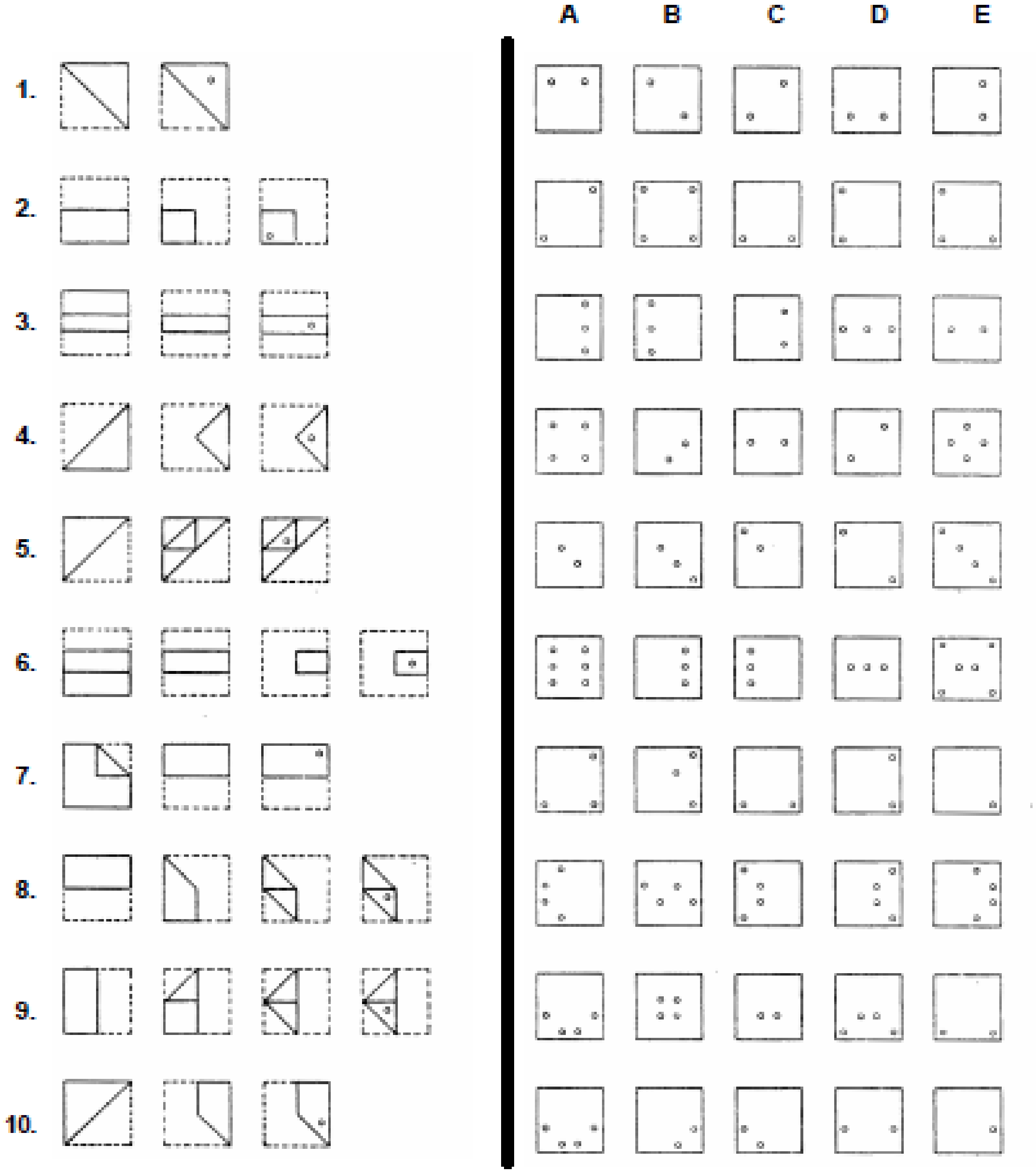
Part 1 (3 minutes)



DO NOT GO ON TO THE NEXT PAGE UNTIL ASKED TO DO SO.

STOP.

Part 1 (3 minutes)



DO NOT GO BACK TO PART 1, AND

DO NOT GO ON TO THE NEXT PAGE UNTIL ASKED TO DO SO.

STOP.

APPENDIX G

INSTRUCTIONS FOR NSE CONDITIONS

Slide 1/2

In this experiment you were reading a series of texts and viewing some pictures on the computer. Your goal is to understand these materials as best as possible.

After each slide you will be given time to reflect and write down any notes or thoughts that you feel may be helpful in to help you remember the material.

We would like you to **write on the sheets** provided after every slide as you progress through the material. Please use a separate page for every slide.

Please hit the <RIGHT ARROW KEY> to move to the next slide.

Slide 2/2

Each slide in the presentation is automatically timed, so please **do not touch the key board once the presentation begins**.

Please raise your hand to notify the experimenter when you are ready to continue.

APPENDIX H

INSTRUCTIONS FOR SE CONDITIONS

Slide 1/2

In this experiment you were reading a series of texts on the computer. Your goal is to understand this material as best as possible.

The text is presented one slide at a time so that you will have time to really think about what information each slide provides and how this relates to what you have already read. We would like you to silently read each slide and then write a **self-explanation**, what it means to you. That is, what new information does each slide provide for you, how does it relate to what you've already read, does it give you a new insight into your understanding of how lightning is formed, or does it raise a question in your mind. Tell us what is going through your mind, even if it seems unimportant.

We would like you to **write your explanations on the sheets** provided, after every slide as you progress through the material. Please use a separate page for every slide.

Please hit the <RIGHT ARROW KEY> to move to the next slide.

Slide 2/2

Each slide in the presentation is automatically timed, so please **do not touch the key board once the presentation begins**.

Please raise your hand to notify the experimenter when you are ready to continue.

APPENDIX I

LIGHTNING FORMATION TEXT

Lightning can be defined as the discharge of electricity resulting from the difference in electrical charges between the cloud and the ground. Warm moist air near the earth's surface rises rapidly. As the air in this updraft cools, water vapor condenses into water droplets and forms a cloud. The cloud's top extends above the freezing level. At this altitude, the air temperature is well below freezing, so the upper portion of the cloud is composed of tiny ice crystals. Eventually, the water droplets and ice crystals become too large to be suspended by updrafts. As raindrops and ice crystals fall through the cloud, they drag some of the air in the cloud downward, producing downdrafts. The rising and falling air currents within the cloud may cause hailstones to form. When downdrafts strike the ground, they spread out in all directions, producing gusts of cool wind people feel just before the start of rain. Within the cloud, the moving air causes charges to build, although scientists do not fully understand how it occurs. Most believe that the charge results from the collision of the cloud's light, rising water droplets and tiny pieces of ice against hail and other heavier, falling particles. The negatively charged particles fall to the bottom of the cloud, and most of the positively charged particles rise to the top.

The first stroke of a flash of ground-to-cloud lightning is started by a stepped leader. Many scientists believe that it is triggered by a spark between the areas of positive and negative charges. A stepped leader moves downward in a series of steps, each of which is about 50 yards long and lasts for about 1 millionths of a second. As the stepped leader nears the ground, positively charged upward-moving leaders travel up from such objects as trees and buildings to meet the negative charges. Usually, the upward-moving leader from the tallest object is the first to meet the stepped leader and complete a path between the cloud and earth. The two leaders generally meet about 165 feet above the ground. Negatively charged particles then rush from the cloud to the ground along the path created by the leaders. It is not very bright and usually has many branches.

As the leader stroke nears the ground, it induces an opposite charge, so positively charged particles from the ground rush upward along the same path. This upward motion of the current is the return and it reaches the cloud in about 70 microseconds. A return stroke produces the bright light that people notice in a flash of lightning, but the current travels so quickly that its upward motion cannot be perceived. The lightning flash usually consists of an electrical potential of several million volts. The air along the lightning channel is heated briefly to a very high temperature. Such intense heating causes the air to expand explosively, producing a sound wave we call thunder. A flash of lightning may end after one return stroke. In most cases, however, dart leaders which are similar to stepped leaders, carry more negative charges from the cloud down the main path of the previous stroke. Each dart leader is followed by a return stroke. This process commonly occurs 3 or 4 times in one flash, but can occur more than 20 times. People can sometimes see the individual strokes of a flash. At such times the lightning appears to flicker.

TABLE

Table 1

Review of Sample Sizes

Study	Treatment	n (mean per condition)
Ainsworth & Loizou (2003)	Text vs diagram, SE	10
Chi, De Leeuw, Chiu, & LaVancher (1994)	Self-Explaining	14
Chiou & Lang (2009)	Self-explaining (control vs. no prompt vs. content free prompt vs. content-related prompt	15.5
Aleven & Koedinger (2002)	Computer based SE prompting	12
Griffin, Theide, & Wiley (2008)	Read once vs reread vs. SE	30.6
Hilbert & Renkl (2009)	Practice vs. example vs. example with SE	25
Sum (mean)		107.1 (17.85)

Table 2
Slide Timing

Slide	Words	Word %	Read time in sec	SE time in sec
Text1	79	13.933	24	120
Text2	74	13.051	22	120
Text3	69	12.169	21	120
Text4	149	26.279	45	120
Text5	196	34.568	59	120
Total	567	100	170	600

Table 3

Predictor and Criterion Variables

Predictor Variables	Description
Spatial ability	Pre-test score on the paper folding task
Working Memory Capacity	Either (1) traditional OSPAN score or (2) total correct letters recalled.
Self-Explaining	Refers to the comparison of conditions in which a participant engaged in self-explaining or not
Illustration	Refers to the comparison of conditions in which a participant was exposed to a text-accompanying illustration or not
Prior knowledge	Multiple choice pre-test score
Criterion variables	Variables that are being predicted from the regression equation
Multiple choice posttest	15-item multiple choice test designed to knowledge comprised of questions designed to assess differing levels of knowledge
Explicit-Deep	Questions requiring participant to answer by integrating information from various pieces of explicitly stated information in the learning presentation
Implicit-Deep	Questions requiring participants to answer by inferring information not explicitly mentioned in the learning presentation
Explicit-Shallow	Questions requiring participants to answer based on information explicitly mentioned in the learning presentation without integration of other pieces of information
True-False posttest	20-item true-or-false test measuring shallow knowledge from participants
Retention/recall	Open-ended recall question taken from Mayer
Transfer total	Sum of points accumulated from 4 transfer questions taken from Mayer

Table 4

Pearson Correlation Matrix of Dependent Variables

		Mayer Pretest	Pre M/C	Post Exp-D	Post Exp-S	Post Imp-D	Post M/C	Pre Spatial	True/ False	Reten.	Trans. Total	WMC
Mayer pretest	Pearson Correlation	1	.222**	.119	.244**	.212**	.242**	.133	.087	.064	.085	.113
Pre M/C	Pearson Correlation	.222**	1	.355**	.406**	.436**	.507**	.254**	.407**	.014	.074	.060
Post Exp-D	Pearson Correlation	.119	.355**	1	.351**	.483**	.796**	.316**	.420**	.048	-.013	.018
Post Exp-D	Pearson Correlation	.244**	.406**	.351**	1	.426**	.754**	.442**	.536**	.007	.030	.074
Post Imp-D	Pearson Correlation	.212**	.436**	.483**	.426**	1	.797**	.332**	.360**	.018	.077	-.103
Post M/C	Pearson Correlation	.242**	.507**	.796**	.754**	.797**	1	.464**	.563**	.032	.037	-.001
Pre Spatial	Pearson Correlation	.133	.254**	.316**	.442**	.332**	.464**	1	.380**	.139	.102	.158*
True/False	Pearson Correlation	.087	.407**	.420**	.536**	.360**	.563**	.380**	1	-.009	-.033	.074
Retent.	Pearson Correlation	.064	.014	.048	.007	.018	.032	.139	-.009	1	.620**	-.072
Trans. Total	Pearson Correlation	.085	.074	-.013	.030	.077	.037	.102	-.033	.620**	1	-.075
WMC	Pearson Correlation	.113	.060	.018	.074	-.103	-.001	.158*	.074	-.072	-.075	1

**. Correlation is significant at the 0.01 level(2-tailed)

Table 5

Hypothesis 1 Hierarchical Regression Analysis: True/False Test as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.332	.067	4.93***	.332	.068	4.92***	.339	.068	4.99***
SA	.295	.067	4.93***	.295	.068	4.36***	.297	.068	4.39***
SE Contrast				-.005	.065	-.075	-.005	.065	-.070
Self-explanation x Spatial ability							-.068	.066	-1.03
R^2		.248			.248			.252	
F for change in R^2		29.11***			.006			1.06	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 6

Hypothesis 1 Hierarchical Regression Analysis: Multiple Choice as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.417	.061	6.79***	.414	.061	6.80***	.413	.061	6.74***
SA	.358	.061	5.84***	.354	.061	5.81***	.354	.061	5.79***
SE Contrast				-.110	.059	-1.87*	-.110	.059	-1.87*
Self-explanation x Spatial ability							.008	.059	.140
R^2		.377			.390			.390	
F for change in R^2		53.63			3.50*			.019	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 7

Hypothesis 1 Hierarchical Regression Analysis: Open-ended Retention as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	-.022	.077	-.292	-.022	.077	-.288	-.024	.078	-.309
SA	.144	.077	1.88*	.145	.077	1.88*	.144	.077	1.86*
SE Contrast				.013	.075	.171	.013	.075	.169
Self-explanation x Spatial ability							.019	.075	.258
R^2		.020			.020			.020	
F for change in R^2		1.776			.029			.067	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 8

Hypothesis 1 Hierarchical Regression Analysis: Open-ended Transfer as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.051	.077	.664	.052	.077	.675	.045	.078	.575
SA	.089	.077	1.15	.090	.077	.664	.088	.077	1.13
SE Contrast				.045	.075	.599	.044	.075	.594
Self-explanation x Spatial ability							.080	.075	1.07
R^2		.013			.015			.021	
F for change in R^2		1.15			.359			1.14	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 9

Hypothesis 2 Hierarchical Regression Analysis: True/False Test as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.332	.067	4.93***	.344	.066	5.24***	.346	.066	5.24***
SA	.295	.067	4.38***	.278	.066	4.23***	.280	.066	4.24***
PIC Contrast				-.212	.064	-3.33***	-.266	.153	-1.73***
Self-explanation x Illustration							.060	.153	.388
R^2		.248			.292			.293	
F for change in R^2		29.11***			11.06***			.150	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 10

Hypothesis 2 Hierarchical Regression Analysis: Multiple Choice Test as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.417	.061	6.79***	.421	.061	6.87***	.423	.062	6.87***
SA	.358	.061	5.82***	.351	.061	5.73***	.353	.062	5.37***
PIC Contrast				-.082	.059	-1.38	-.142	.143	-.996
Self-explanation x Illustration							.067	.143	.467
R^2		.377			.384			.385	
F for change in R^2		53.633***			1.89			.218	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 11

Hypothesis 2 Hierarchical Regression Analysis: Open-ended Retention as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	-.022	.077	-.292	-.030	.076	-.395	-.039	.076	-.508
SA	.144	.077	1.88*	.156	.077	2.04**	.146	.076	1.92*
PIC Contrast				.143	.074	1.93*	.419	.177	2.37**
Self-explanation x Illustration							-.303	.177	-1.71*
R^2		.020			.040			.056	
F for change in R^2		1.78			3.73*			2.93*	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 12

Hypothesis 2 Hierarchical Regression Analysis: Open-ended Transfer as Criterion

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.051	.077	.664	.044	.077	.568	.040	.077	.521
SA	.089	.077	1.15	.100	.077	1.30	.096	.077	1.25
PIC Contrast				.142	.074	1.90*	.254	.179	1.42
Self-explanation x Illustration							-.124	.179	-.691
R^2		.013			.033			.035	
F for change in R^2		1.15			3.62*			.478	

Note: Spatial ability was centered at its mean

*p < .10. **p < .05. ***p < .01

Table 13

Hypothesis 3a Hierarchical Regression Analysis: True/False as Criterion; Traditional OSPAN as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.404	.069	5.89***	.404	.069	5.87***	.404	.069	5.86***
Traditional OSPAN	.050	.069	.731	.049	.069	.711	.049	.069	.708
SE Contrast				-.009	.069	-.130	.048	.203	.238
Self-explanation x WMC							-.061	.203	-.300
R^2		.168		.169			.169		
F for change in R^2		17.93***		.017			.090		

*p < .10. **p < .05. ***p < .01

Table 14

Hypothesis 3a Hierarchical Regression Analysis: Multiple Choice Test as Criterion; Traditional OSPAN as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.509	.065	7.86***	.506	.064	7.87***	.507	.065	7.85***
Traditional OSPAN	-.031	.065	-.485	-.045	.065	-.697	-.045	.065	-.697
SE Contrast				-.127	.065	-1.96*	-.063	.190	-.329
Self-explanation x WMC							-.068	.190	-.358
R^2		.258			.274			.275	
F for change in R^2		30.85***			3.83*			.128	

*p < .10. **p < .05. ***p < .01

Table 15

Hypothesis 3a Hierarchical Regression Analysis: Open-ended Retention as Criterion; Traditional OSPAN as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.019	.075	.246	.019	.075	.246	.018	.076	.244
Traditional OSPAN	-.073	.075	-.969	-.073	.076	-.960	-.073	.076	-.985
SE Contrast				.000	.076	.004	-.009	.222	-.041
Self-explanation x WMC							.010	.222	.045
R^2		.005			.005			.005	
F for change in R^2		.487			<.000			.002	

*p < .10. **p < .05. ***p < .01

Table 16

Hypothesis 3a Hierarchical Regression Analysis: Open-ended Transfer as Criterion; Traditional OSPAN as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.078	.075	1.05	.079	.075	1.06	.080	.075	1.06
Tradional OSPAN	-.080	.075	-1.06	-.076	.075	-1.01	-.076	.076	-1.001
SE Contrast				.034	.075	.448	.160	.221	.723
Self-explanation x WMC							-.134	.221	-.607
R^2		.012			.013			.015	
F for change in R^2		1.05			.201			.369	

*p < .10. **p < .05. ***p < .01

Table 17

Hypothesis 3b Hierarchical Regression Analysis: True/False Test as Criterion; Total Correct Letters as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.501	.065	7.68***	.498	.065	7.69***	.499	.065	7.67***
Total Correct Letters	.053	.065	.818	.044	.065	.680	.046	.066	.697
SE Contrast				-.118	.064	-1.84*	-.059	.301	-.196
Self-explanation x WMC							-.060	.301	-.201
R^2		.260			.274			.274	
F for change in R^2		31.14***			3.37*			.040	

*p < .10. **p < .05. ***p < .01

Table 18

Hypothesis 3b Hierarchical Regression Analysis: Multiple Choice Test as Criterion; Total Correct Letters as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.501	.065	7.67***	.498	.065	7.69***	.499	.065	7.67***
Total Correct Letters	.053	.065	.818	.044	.065	.680	.046	.066	.697
SE Contrast				-.118	.064	-1.84*	-.059	.301	-.196
Self-explanation x WMC							-.060	.301	-.201
R^2		.260			.274			.258	
F for change in R^2		31.14			3.37*			.040	

*p < .10. **p < .05. ***p < .01

Table 19

Hypothesis 3b Hierarchical Regression Analysis: Open-ended Retention as Criterion; Total Correct Letters as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.021	.076	.276	.021	.076	.276	.020	.076	.261
Total Correct Letters	-.052	.076	-.686	-.052	.076	-.678	-.053	.077	-.696
SE Contrast				.004	.076	.056	-.068	.353	-.193
Self-explanation x WMC							.074	.352	.210
R^2		.003			.003			.003	
F for change in R^2		.253			.003			.044	

*p < .10. **p < .05. ***p < .01

Table 20

Hypothesis 3b Hierarchical Regression Analysis: Open-ended Transfer as Criterion; Total Correct Letters as WMC

	Model 1			Model 2			Model 3		
Variable	*β*	*SE*	*t*	*β*	*SE*	*t*	*β*	*SE*	*t*
Pretest	.084	.075	1.119	.085	.076	1.126	.088	.076	1.159
Total Correct Letters	-.082	.075	-1.087	-.079	.076	-1.045	-.074	.076	-.968
SE Contrast				.036	.075	.479	.232	.351	.661
Self-explanation x WMC							-.200	.350	-.572
R^2		.012			.013			.015	
F for change in R^2		1.08			.229			.327	

*p < .10. **p < .05. ***p < .01

Table 21

Hypothesis 4 Simultaneous Regression Results

	Pretest				
Learning measure	*F*	R^2	*B*	*SE*	*t*
True/False	35.41***	.166	.407	.068	22.33
Multiple Choice*	61.73***	.258	.507	.065	7.86
Retention	.036	<.001	.014	.075	.189
Transfer Total	.972	.005	.074	.075	.986

****=Significant at the .001 level*

Table 22

Descriptive Statistics of Different Groups

Learning Measure	Group NSE-NI n=46 Mean (SD) performance	Group NSE-I n=47	Group SE-NI n=36	Group SE-I n=51
Pretest Multiple-Choice	5.91 (2.71)	6.21 (2.46)	6.61 (2.23)	5.92 (1.99)
Posttest Multiple-Choice	8.35 (2.95)	8.91 (3.16)	9.22 (3.03)	9.61 (2.74)
Pre Spatial	5.17 (5.54)	5.51 (2.52)	5.36 (2.45)	5.67 (2.50)
Traditional OSPAN	44.50 (18.81)	51.53 (16.24)	50.75 (19.67)	52.94 (17.70)
Total Correct Letters	58.28 (16.02)	63.13 (12.29)	61.25 (16.11)	64.12 (10.48)
True-False Total	13.63 (2.67)	14.06 (2.65)	12.86 (2.79)	14.78 (2.12)
Retention	2.78 (2.15)	2.51 (2.72)	3.19 (2.04)	2.20 (2.29)
Transfer Total	2.98 (1.99)	2.57 (2.14)	3.00 (1.80)	2.35 (1.75)

Table 23

Descriptive Statistics of Different Groups

Learning Measure	Group NSE n=46 Mean (SD) performance	Group NI n=47	Group SE n=36	Group I n=51
Pretest Multiple-Choice	5.91 (2.71)	6.22 (2.52)	6.61 (2.23)	6.06 (2.22)
Posttest Multiple-Choice	8.63 (3.05)	8.73 (3.00)	9.45 (2.87)	9.28 (2.96)
Pre Spatial	5.17 (5.54)	5.26 (2.49)	5.36 (2.45)	5.59 (2.50)
Traditional OSPAN	48.05 (17.82)	47.24 (19.33)	52.03 (18.46)	52.27 (19.94
Total Correct Letters	60.73 (14.39)	59.59 (16.03)	62.93 (13.10)	63.64 (11.34)
True-False Total	13.85 (2.65)	13.29 (2.73)	13.99 (2.59)	14.44 (2.40)
Retention	2.65 (2.44)	2.96 (2.10)	2.61 (2.23)	2.35 (2.50)
Transfer Total	2.77 (2.07)	2.99 (1.90)	2.62 (1.79)	2.46 (1.94)