Graph Comprehension:

Difficulties, Individual Differences, and Instruction

by

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This work is dedicated to my paternal grandmother, Rachel Greenberg, whose inner strength and spirit have been a true inspiration. As a holocaust survivor, she has always promoted the pursuit of knowledge and she taught me that education is one of the most important things in life, as education, once achieved, cannot be taken away from you. In pursuing my own goals, I thank her for acting as a role model for accomplishment in the face of adversity. From her life lessons, I know that no matter how hard the path, it is imperative to hope and to continue working towards my goals. Although I do not have the opportunity to see her often, she is always in my heart.

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Table of Contents

List of Figures

List of Tables

List of Appendices

Abstract

Graphs are pervasive in our daily lives (e.g., newspapers, textbooks, scientific journals, classrooms), and there is an implicit assumption that, although they are not explicitly taught graphical literacy, people are capable readers of graphs. However, interpreting multivariate data presented graphically is extremely challenging and few, if any, instructional tools or guidelines exist for teaching complex graph interpretation. Furthermore, designing graphs of multivariate data to make them more interpretable and instructing individuals to interpret graphs are both complicated by the fact that numerous factors likely influence the graph interpretation process: the type of display, individuals' initial graphical literacy skills, their working memory (WM) capacity, and their attitudes or dispositions towards thinking and avoiding belief bias. The goals of the current research were to determine: (1) how well people comprehend main effects and interactions in complex multivariate data presented graphically and the extent to which some graph format characteristics influence the process; (2) whether students can be taught to interpret main effects and interactions in complex graphs and what might comprise such an instructional tutorial; and (3) the role of individual differences in complex graph comprehension. To address these questions, five experiments were conducted. Experiment 1 examined how much people attend to graphs, and whether the existence of a graph to summarize data already described in a text help them remember or understand the data. Experiments 2 and 3 examined students' interpretation of multivariate graphs in a self-paced, open-ended task and in immediate and long-term memory tasks, and the effect of graph format in these various contexts. Finally, Experiments 4 and 5 examined whether a tutorial could be an effective instructional tool for improving graph skills, and how instruction is differentially impacted by individual differences. In general, individual differences emerged as extremely influential factors in graph comprehension and the training of graph skills, whereas graph format did not play a key role in the current research. Additional research is suggested for further development of the tutorial as an educational resource, and educators should promote enjoyment of cognitive work in the classroom to increase benefit of instruction.

CHAPTER 1:

INTRODUCTION

Why Are Graphs Important?

In the current "Information Age", when a lot of complex data is readily accessible at the press of a button, people are increasingly facing the task of analyzing and communicating such information. Diagrams, graphs, and pictures are frequently used to communicate information to learners in textbooks, research journals, power point presentations, web pages, and educational software. Moreover, visualizations are common in news sources such as *USA Today* and the *New York Times* and are used to convey different types of data from which readers may make decisions such as who to vote for or whether or not to consume red wine. Certainly, the use of graphs to depict quantitative data has increased over the years, especially for academic journals and newspapers (Zacks, Levy, Tversky, & Schiano, 2002).

The current research focuses specifically on graphs, especially those of complex data, due to the following reasons. Although there has been an increase in research relating to graph comprehension over the years, much of this research has corresponded to simpler data sets that contain two-variable data or a small number of data points, and conclusions from these studies do not usually generalize to graph comprehension of more complex multivariate data (Canham & Hegarty, 2010; Ratwani & Trafton, 2008; Shah, Freedman, & Vekiri, 2005; Trafton et al., 2000). Science standards (NSTA; NRC) emphasize the importance for students to conceptually understand complex models in which two or more variables interact to create outcomes. Additionally, psychologists and other social scientists commonly use factorial designs in their experiments, which necessitates that students be able to read and interpret complex data. Such data sets may contain complicated relationships between variables, or main effects and interactions. Main effects are the effects of one independent variable (a variable that was manipulated) on the dependent variable (the variable being measured) while ignoring the effects of all other independent variables. Interactions occur when the effect of one independent variable on the dependent variable changes depending on the level of another independent variable.

Furthermore, there seems to be an expectation that readers or students are capable of understanding such complex graphs even when not explicitly taught to do so. For example, I recently analyzed the contents of 30 psychology textbooks, written primarily for undergraduate students ranging in publication dates from 1997 to 2013. These textbooks included nine General or Introductory Psychology books, eight Cognitive Psychology books, eight Research Methods books, two Cognitive Neuroscience books, two Social Psychology books, and one Abnormal Psychology book. I found 1,345 graphs depicting quantitative data. That is, approximately 45 graphs were present per textbook. Of these graphs, at least 540 of them could be considered relatively complex as they contained factorial designs of 2x2 or greater, and only a very small number of these (less than 5) were extremely complex with three independent variables. However, some of the graphs that would normally be considered extremely complex with three independent variables are not included in this count, as they were shown side-by-side in separate panels, possibly in the attempt to simplify the graph complexity or highlight different aspects of the data. Additionally, at least 700 of the graphs contained labels, at least 170 of them contained legends, and at least 370 of them contained both labels and legends. Moreover, at least 630 of them were line graphs and at least 710 of them were bar graphs. Thus, even in perusing a relatively small sample of textbooks, it is clear that graphs are prevalent and that students are expected to understand them. A table describing the information from this analysis is presented in Table 1.1.

Graph Characteristics and Difficulty

Given the underlying assumption that college students are capable of interpreting and understanding such graphs in textbooks and other contexts, it is important to determine whether this is a fair expectation. One reason why graphs are used so extensively is a belief (often misguided) that they make quantitative data easier to understand (Linn, Chang, Chiu, Zhang, & McElhaney, 2010; MacDonald-Ross, 1977; Tversky, 2001;

Winn, 1987). This is mostly true when concepts or important quantitative information are explicitly depicted in graphs or other visualizations so that minimal cognitive processing is required (Larkin & Simon, 1987; Pinker, 1990). However, most graphs are actually not so easy to understand and require mental transformations and other cognitive processes to comprehend them. How difficult is graph comprehension really?

Graph comprehension is generally thought to include three main components (Bertin, 1983; Carpenter & Shah, 1998; Pinker, 1990; Shah & Carpenter, 1995). Viewers first encode and identify the important visual features of the graph. This first process can be affected by inherent perceptual biases and limitations that influence the accuracy (e.g., Cleveland & McGill, 1984, 1985; Legge, Gui, & Luebker, 1989; Spence, 1990) and grouping of the information encoded (e.g., Carpenter & Shah, 1998; Shah, Mayer, & Hegarty, 1999). Then these features are mapped onto the corresponding quantitative or conceptual relationships in the second component. This process is influenced by what was encoded in the first process, how easy it is to map visual features to their referents, and individuals' graph schemas, or general knowledge about graphs (Pinker, 1990). Finally, these quantitative or conceptual relationships are associated with the referents or the variables of the graph, and this association can be influenced by expectations (Shah, 1995; Shah & Shellhammer, 1999). These three processes are both incremental and interactive, in that viewers may complete these three processes for different parts of the graph, and the more complex the graph, the longer it will take to interpret as these processes will occur for each conceptual relationship (Carpenter & Shah, 1998).

Graph comprehension is unlike object recognition in that it is harder, it can take a long time, and is limited with regards to how much viewers can process at a time. Individuals can only keep track of so many variables at a time, and it seems that the upper limit for processing load is four variables given that performance with five variables is at chance levels (Halford, Baker, McCredden, & Bain, 2005). Halford et al. (2005) manipulated processing load while keeping memory load constant, in order to examine performance on 2, 3, or 4-way interactions in bar graphs. Accuracy and speed decrease with increasing order of interaction, such as moving from a 2-way interaction to a 3-way interaction or from a 3-way interaction to a 4-way interaction. Processing load difficulties were not apparent until four variables were introduced, and persisted to graphs that included five variables.

Indeed, interpreting multivariate data presented graphically is very challenging (Halford et al., 2005; Shah & Carpenter, 1995; Shah & Freedman, 2011), even for those who may be considered experts, such as graduate students with extensive research experience (Shah & Carpenter, 1995). Comprehending moderately complex graphs may take as long as, or even longer than, comprehending similar information presented textually (Carpenter & Shah, 1998; Ratwani, Trafton, & Boehm-Davis, 2008). In one study, for example, it took viewers from 30 seconds to a minute to interpret a graph; that is about the time it takes to read a short paragraph and much longer than the time needed to view an object (Carpenter & Shah, 1998). Even simple graphs can be difficult to interpret (Culbertson & Powers, 1959; Guthrie, Weber, & Kimmerly, 1993; Romberg, Fennema, & Carpenter, 1993; Vernon, 1946, 1950), particularly when important information is less obviously depicted, thus leading to more errors and requiring more effort (Bell & Janvier, 1981; Culbertson & Powers, 1959; Gattis & Holyoak, 1996; Guthrie et al., 1993; Leinhardt, Zaslavsky, & Stein, 1996; Maichle, 1994; Shah et al., 1999; Shah & Carpenter, 1995; Vernon, 1946, 1950). Graphs found in textbooks are not excused either, as some studies have found that readers often misinterpret or fail to determine the author's intended message (e.g., Shah et al., 1999). Moreover, statistics and research methods teachers frequently report that students have difficulty with such graphs and that interpretation of such data is difficult to teach. Additionally, graph comprehension can be difficult in that it is influenced by a variety of bottom-up and top-down factors, including perceptual organization (Shah et al., 1999), graph format (Ainsworth, 2006; Canham & Hegarty, 2010; Cheng, 1999; Shah et al., 1999; Shah & Freedman, 2011; Simkin & Hastie, 1987), domain knowledge (Freedman & Shah, 2002; Lowe, 1993; Shah & Freedman, 2011), and experience with graph conventions (Korner, 2005; Shah et al., 2005).

Graph Comprehension as a Construct and its Relation to Instruction

Graph comprehension has been defined by Friel, Curcio, & Bright (2001) as a reader's "ability to derive meaning from graphs created by others or by themselves" (p.

132), and is thought to develop gradually through practice in building and using multiple types of graphs in contexts that require the learner to make sense of the data. Graph comprehension has also been broken up into multiple competence levels (Curcio, 1989; Friel et al., 2001): (1) the basic skill of reading the data or finding specific information in a graph; (2) the intermediate skill of reading between the data, or finding relationships in the data presented in a graph; and (3) the advanced skill of reading beyond the data, or making inferences and predictions based on the data.

Although a considerable amount of research has been conducted on graph comprehension across multiple domains, including mathematics, statistics, decision-making, information visualization, and cognitive psychology, insufficient crosstalk has occurred between fields communicating findings, and I have yet to find an evidence-based consensus or guide for how to teach comprehension of complex multivariate graphs. Most guides for teaching graphs seem to impart how to use specific software packages to create graphs of different types or focus solely on graph display and design (e.g., Kosslyn, 1994; Tufte, 1983), but do not directly address instruction of graph comprehension. Fry (1981) and colleagues (e.g., Singer & Donlan, 1980) have suggested that reading comprehension and graph comprehension are analogous, and thus reading instructors should apply a similar approach to graph comprehension that they would use for reading lessons. Still others have suggested direct and indirect implications of graph comprehension research for teaching graphical literacy (e.g., Shah & Hoeffner, 2002), but do not provide very explicit guidelines for how these implications would manifest in instruction within the classroom. Some guidelines have been suggested regarding when and what kinds of graphs (i.e., complexity) should be introduced to students (e.g., Friel et al., 2001), but these were intended for students in grades K-8 and do not approach the level of complexity inherent in multivariate data containing main effects and interactions. Some researchers have also noted that until a better understanding of how the visual system extracts relations from "chunked" information in graphs has been reached, instructors will be unable to teach students how to parse graphical relationships (Franconeri, Uttal, & Shah, 2011). The current models and frameworks posited in relation to these perceptual processes have either been too specific to one type of graph (Ratwani et al., 2008) or unsupported by direct evidence (e.g., Gillan & Lewis, 1994; Simkin & Hastie, 1987).

Perhaps one reason why students find graph comprehension relatively hard is because graphical literacy had not previously been a dedicated part of the school curriculum, but rather was covered piecemeal as parts of other curricula or study skills (Fry, 1981). Graph instruction is made even more difficult by some teachers' limited graph skills or low competence in building and interpreting graphs (Batanero, Arteaga, & Ruiz, 2010; Bruno & Espinel, 2009; Gonzalez, Espinel, & Ainley, 2011; Monteiro & Ainley, 2007). More specifically, some teachers fail to read between the data or read beyond the data (Arteaga & Batenero, 2011). Although these studies were primarily conducted with prospective primary school teachers, they highlight the issue of instructor knowledge and how critical it is for teachers to receive the necessary training to increase their knowledge of and competence with graphs in order to provide students with effective instruction. Students cannot be expected to learn graph comprehension skills if their instructors do not have the requisite knowledge or competence to teach them. Friel et al. (2001) also make brief note of this important point, but make no recommendations for how this would be accomplished other than to suggest the use of a manual for elementary teachers to help them learn about statistics (Friel & Joyner, 1997). Therefore, a guide or tutorial that provides instruction for complex graph comprehension would be a valuable resource or tool for both teachers and students, especially as prior focus has been K-8 teachers as opposed to high school and college instructors.

What Makes a "Good" Visualization or Graph?

Because of the increasing importance of visualizations like graphs, there has been an increasing amount of research on the psychological processes involved in visualization comprehension as well as the factors that make visualizations easy or difficult to understand and remember. A major guideline developed based on this research is that visualizations should simplify cognitive processes while emphasizing perceptual processes in an attempt to reduce cognitive load on the part of the learner. According to the Cognitive Efficiency View, visualizations such as graphs should present data as clearly as possible by reducing distracting or irrelevant visual elements or information (e.g. Bertin, 1983; Kosslyn, 1989; Pinker, 1990; Tufte, 1983). This commonly held belief espouses that graphs should include no "chart junk" (i.e., embellishments unessential to understanding the data), reduce cognitive processing, and rely on perceptual processing rather than conceptual. Similarly, Canham & Hegarty (2010) suggest that graphs should provide only task-relevant information (i.e., information needed for the current task), especially when graphs are intended for those with limited domain knowledge, as extraneous task-irrelevant information can impair task performance. This could be because viewers are distracted and have to suppress irrelevant information in a graph, particularly if the superfluous information is salient or interesting (Sanchez & Wiley, 2006). Such additional processing may tax cognitive load (Sweller & Chandler, 1994), especially for students with limited domain knowledge to help them ascertain relevant from irrelevant information in the graph.

Yet, as more recent evidence suggests, these claims may not be uniformly true (see Hullman, Adar, & Shah, 2011 for a review). For example, in one study (Bateman, Mandryk, Gutwin, Genest, McDine, & Brooks, 2010) participants were asked to view and remember data from one of two graph types, "Holmes" graphs (embellished graphs) or plain graphs. Participants not only preferred the embellished graphs, but also remembered the data from the "Holmes" graphs just as well as plain graphs at immediate recall and better than plain graphs at long-term recall two to three weeks later. This prompts the question of why sometimes deviating from the Cognitive Efficiency View can actually be better for learning. Hullman and colleagues (2011) proposed the idea that, in some cases, visualizations that require more difficult cognitive processing rather than relying primarily on perceptual inferences may have some advantages. Thus, the notion of desirable difficulties may be appropriate with regards to visualizations (see Linn et al., 2010 for a similar argument).

Relating the Notion of "Desirable Difficulties" to Graphs

Desirable difficulties are learning activities that generally slow learning and often increase errors in the short-term, but improve learning over the long-term (Bjork, 1994; Bjork & Bjork, 2011). The term "desirable difficulties" is an umbrella term as there is a rather broad range of activities or effects that fall into this category, including generation (e.g., Hirshman & Bjork, 1988; Jacoby, 1978; Slamecka & Graf, 1978), testing or retrieval practice (e.g., Roediger & Karpicke, 2006), spacing (e.g., Kornell, 2009, Rawson & Dunlosky, 2011), interleaving (e.g., Kornell & Bjork, 2008; Rohrer & Taylor, 2007; Shea & Morgan, 1979), and varying learning conditions or contexts (e.g., Kerr & Booth, 1978; Smith, Glenberg, & Bjork, 1978). Following from the research in this domain, perhaps adding difficulties to processing can be beneficial or "desirable" to visualization or graph users for at least three reasons. First, fluency or ease of reading a graph can give viewers a strong but false sense of understanding (Linn et al., 2010). Second, "easy" displays are processed passively rather than actively (e.g., Mayer, Hegarty, Mayer, & Campbell, 2005). Because "easy" displays require less cognitive effort, reading such displays is an automatic perceptual process that may lead to shallow rather than deep processing of the data presented in the graph. Third, learners may spend more time on harder to process material, perhaps in part because the more "difficult" display is more aesthetically appealing than an "easier" to process, simplified display.

One specific challenge to graph interpretation stems from a large variety of design choices, such as the use of labels or legends. Labels are favored in the graph literature (e.g., Carpenter & Shah, 1998; Gillan, Wickens, Hollands, & Carswell, 1998; Kosslyn, 1994; Vaiana & McGlynn, 2002) because they fit with the Cognitive Efficiency View in that they simplify the presented information (i.e., are easy to read and comprehend) and reduce cognitive demand (i.e., labels are thought to "offload" cognitive demand as they are less working memory demanding). Additionally, the use of labels has generally resulted in improved accuracy and increased speed of graph comprehension (e.g., Culbertson & Powers, 1959; Lohse, 1993; Milroy & Poulton, 1978). However, legends may function as a "desirable difficulty" in some contexts given that they require additional search processes to identify different parts of the graphs (i.e., mapping lines or bars with referents). Legends also slow down the learning process, increase the working memory load (i.e., are more cognitively demanding), and change the sequential processing or the order in which people look at different parts of a graph (legends can provide key grouping principles or organization).

The Role of Individual Differences

Another challenge in graph comprehension is that of individual differences. Individual differences relating to cognitive skills, such as graphical literacy and working memory capacity, can be important influential factors in graph comprehension. For example, college students unfamiliar with graphs take a long time, rely on general knowledge, and make progressively more mistakes with increasing graph complexity (Carpenter & Shah, 1998). Students, especially those with little graph interpretation experience, tend to rely more on prior knowledge and will therefore make more mistakes if a graph depicts relationships contrary to their expectations (Shah, 1995; Gattis & Holyoak, 1996). Findings such as these further suggest the need for explicit training of graph interpretation skills, especially for such complex data sets. Those with high graph literacy likely know what to do with more difficult graph formats or can more easily learn how to approach them with additional instruction (e.g., a graph tutorial). In contrast, those with low graph literacy would likely require additional instruction or training to improve their graph comprehension skills in order to avoid making more errors due to unfamiliarity with complex graphs or reliance on expectations based on prior knowledge. Thus, in the current research I included the Graph Literacy Scale (Galesic & Garcia-Retamero, 2011; see Appendix A) as a measure of individuals' familiarity wit h various graphs. Although this measure does not include extremely complex multivariate graphs, it does cover a variety of frequently used graph types, including line graphs, bar graphs, pie charts, and icon arrays. The scale also measures the three main graphical comprehension skills (Curcio, 1987; Friel et al., 2001) of reading the data, reading between the data, and reading beyond the data.

Working memory (WM) span is also expected to play a large role in multivariate graph comprehension. Individuals with low WM span may be overwhelmed when confronted with complex multivariate graphs, as there are many variables to keep track of, and thus might give up because interpretation is too daunting. Additionally, demanding difficulties may only benefit those who have the WM capacity to deal with them. For example, the benefit of introducing difficulties such as legends into a graph could be constrained by the viewer's cognitive skills (Hullman et al., 2011). Thus, added visual difficulties such as legends may be detrimental for low WM span individuals who find complex graphs without such added difficulties already hard to comprehend. The current research therefore included the automated Symmetry Span (SSPAN) task (Unsworth, Heitz, Schrock, & Engle, 2005; see Figure 1.1) as a measure of working memory capacity, with the goal of investigating whether WM capacity mediates performance on graph comprehension tasks, particularly for those graphs with added visual difficulty (i.e., graphs with legends). This working memory span measure requires participants to judge whether pictures are symmetrical, while they are also trying to recall the location of squares on the screen in the correct sequential order. The automated SSPAN task is strongly correlated with the traditional SSPAN task (Unsworth et al., 2005), as well as with other WM measures (e.g., Broadway & Engle, 2010; Shelton, Elliott, Hill, Calamia, & Gouvier, 2009).

Cognitive skills such as graphical literacy and WM capacity have been previously documented as influential for graph comprehension. However, to my knowledge, more dispositional individual differences have not been examined in the context of graph comprehension. For the purposes of the current research these include open-mindedness, need for cognition, and cognitive reflection. It is possible that these factors also mediate graph comprehension, especially in the context of relatively little experience with graphs.

Baron (1985, 1993, 2008) was one of the first to describe actively open-minded thinking (AOT) as a reasoning style. AOT was defined as the tendency to consider new evidence contradictory to a favored belief, to spend sufficient time on a problem rather than give up prematurely, and to carefully reflect on others' opinions when forming one's own. Increased open-mindedness has been associated with better critical thinking skills, as unbiased or objective reasoning about data is widely considered one crucial characteristic of good critical thinking (Stanovich & West, 1997). Furthermore, a decreased susceptibility to belief bias, or an increased ability to divorce prior knowledge from analytical processes, has been associated with increased AOT (e.g., Macpherson & Stanovich, 2007; Sa, West, & Stanovich, 1999; Stanovich & West, 1998). For example, one study exploring the relationship between gaming and critical thinking found that gamers who play strategy related games tend to rate higher on actively open-minded thinking than gamers who play other genres of games (Gerber & Scott, 2011). Given that graph comprehension consists of evaluating data and the relationships present in the data, one might expect open-mindedness to similarly be important for graph comprehension as it is for critical thinking. Individuals with increased open-mindedness, or increased tendency for open-minded thinking and cognitive flexibility, would likely be more willing to try to interpret multivariate graphs, even if they have not encountered such complex graphs before. These individuals may also be more willing to consider data that is inconsistent with their own domain knowledge, rather than misinterpret data due to a reliance on expectations based on prior knowledge. Comparatively, less open-minded individuals may rely on prior beliefs instead of interpreting the data, especially if they have limited experience with graphs and the graphs are more difficult. Furthermore, open-mindedness may impact the effectiveness of instruction, as less open-minded individuals might not appreciate or benefit from graph comprehension training. In the current research I measured open-mindedness with the Actively Open-minded Thinking (AOT) scale (Stanovich & West, 1997, 2007; see Appendix B), in which higher scores indicate a greater tendency for open-minded thinking and cognitive flexibility, while lower scores indicate cognitive rigidity and resistance to belief change.

Need for cognition (NFC), or how likely one is to engage in and enjoy effortful thinking (Cacioppo, Petty, & Kao, 1984), is another attitude that could critically impact graph comprehension. High NFC was thought to reflect a greater likelihood to organize, elaborate on, and evaluate information (Cohen, 1957). This dispositional measure has been reliably associated with better achievement and deliberate or effortful information processing (see Cacioppo, Petty, Feinstein, & Jarvis, 1996). High NFC individuals are less likely to jump to conclusions unsupported by evidence (Kardash & Scholes, 1996), more likely to make accurate judgments (Blais, Thompson, & Baranski, 2005), and are more likely to persist in seeking out or acquiring information helpful to making accurate judgments on estimation or forecasting tasks (Haran, Ritov, & Mellers, 2013). Some research indicates that NFC may be related to self-control capacity in high-school students (Bertrams & Dickhauser, 2009) and that NFC is associated with critical thinking in college undergraduates (e.g., Stedman, Irani, Friedel, Rhoades, & Ricketts, 2009). Some have defined NFC as a measure of intrinsic motivation for engaging in challenging intellectual activity, while also pointing out the possibility that NFC reflects extrinsic motivation such as success or avoidance of failure in an academic context (e.g., Steinhart

& Wyer, 2009). Taken together, NFC could be considered a proxy for cognitive effort or attitude towards completing difficult work, which could be an incredibly informative measure given the established difficulty of graph comprehension. Thus, the current research included the NFC scale (Cacioppo et al., 1996; see Appendix C), in which higher scores indicate a greater tendency to engage in and enjoy thinking. One might expect that high NFC would be associated with better graph comprehension, as understanding complex data may require more cognitive effort. Additionally, those with low NFC may be less likely to seek external help or more likely to give up, while those with high NFC may be more likely to meet and benefit from challenges. Moreover, those who enjoy cognitive challenge would perhaps be more amenable to instruction or training of graph comprehension skills, while those individuals with low NFC would benefit less, or not at all.

Finally, cognitive reflection may also predict performance on graph comprehension tasks. Cognitive reflection is the ability to suppress an intuitive, automatic, or spontaneous incorrect response in order to come up with a more reflective and deliberative correct answer, as measured by the Cognitive Reflection Test (CRT; Frederick, 2005; see Appendix D) in the current research. Cognitive reflection has been associated with avoiding biases (Oechssler, Roider, & Schmitz, 2009) and may be related to the characteristic of searching out potential possibilities prior to making an inference that was one component of Baron's (1985, 1993, 2008) concept of AOT. Individuals demonstrating increased cognitive reflection might make fewer errors in graph comprehension because they are more likely to interpret the actual data presented in multivariate graphs rather than rely on shortcuts or heuristics based on domain knowledge or prior expectations. This measure may also reflect a willingness to work hard interpreting complex graphs, especially when graph comprehension is made more difficult with legends, which could potentially translate to greater benefit or improvement from additional graph instruction or training.

Goals of the Current Research

In sum, it is important to gain a more thorough understanding of graph comprehension for complex multivariate data, both in relation to people's ability to do it and to training or teaching people how to do it better, especially given the frequency with which graphs are encountered in daily life and the implicit expectation that people should be capable readers of such visualizations. Therefore, the current line of research aims to address the following questions: (1) How well do people comprehend main effects and interactions in complex multivariate data presented in graphs, and does graph format play a role (i.e., do legends function as a desirable difficulty)? (2) Can students be trained or taught to better identify and understand main effects and interactions inherent in graphs of complex data sets, and what would comprise such an effective tutorial? (3) What role do individual differences play in complex graph comprehension and the training of these skills?

In order to address these questions, I completed five experiments. In Experiment 1, I determined whether readers benefit from graphs presented alongside textual explanations of data, and if such graphs provide an advantage in comparison to reading the text alone or viewing an irrelevant picture with the text. In Experiments 2 and 3, I examined whether students are able to identify main effects and interactions presented in graphs, and whether this differs with graph format (i.e., labels versus legends), with tasks that involve interpreting or describing presented data in an open-ended context and remembering important aspects of a data set. In Experiments 4 and 5, I investigated whether students understand main effects and interactions in graphs, whether graph comprehension differs by graph format (labels versus legends), and whether students can be trained to better identify and interpret such data using a graph tutorial that I created. In all of these experiments I investigated the role of individual differences, as one interest in the current research is in determining whether certain individual differences mediate people's graph comprehension, their ability to benefit from training, or the potential for difficulties such as legends to be beneficial.

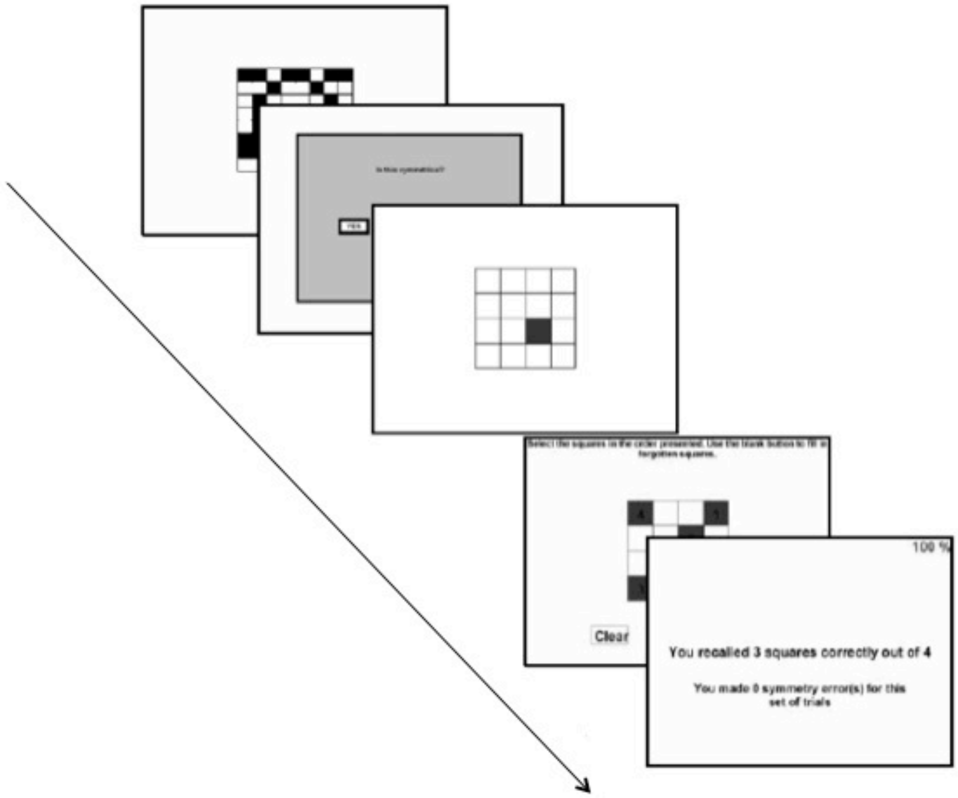


Figure 1.1. **Automated Symmetry Span Task Sample Trial Sequence**. This figure was modified from the one found in Redick et al. (2012).

Table 1.1

Analysis of Graphs in Psychology Textbooks

Book Subject	Number of Textbooks	Total Graphs	Line Graphs	Bar Graphs	Graphs with Labels	Graphs with Legends	Graphs with Labels & Legends
General or Introductory Psychology	9	409	146	263	241	23	137
Cognitive Psychology	8	333	168	165	169	83	37
Research Methods	8	206	139	67	144	16	33
Social Psychology	2	170	43	127	67	10	91
Cognitive Neuroscience	2	205	123	82	75	45	68
Abnormal Psychology	1	22	12	10	8	2	12
Totals	30	1345	631	714	704	179	378

Note. These values are approximations collected from actual psychology textbooks. Not shown are the total number of graphs for each category that contained neither labels nor legends.

CHAPTER 2:

GRAPHS IN TEXTBOOK EXCERPTS

Introduction

Given the widespread usage of graphs across many media (e.g., newspapers, television, textbooks, scientific journals, and even classrooms) and the apparent assumption made by publishers of these media that people are capable readers of graphical information, a critical first question is whether people or students actually benefit from the inclusion of graphs in order to remember the information presented within the text. Thus, it is important to determine whether individuals use information presented in graphs when reading textual information such as an article or textbook that already contains a summary of the data, and, if they do use these graphs, whether the graph is helpful. How does the addition of a graph compare to the inclusion of seductive details such as irrelevant pictures?

According to the seductive details hypothesis, presenting interesting but irrelevant information with a text can be detrimental in remembering the main points of the text, or at best is no better than presenting the text by itself (e.g., Garner, Brown, Sanders, & Menke, 1992; Garner, Gillingham, & White, 1989; Hidi & Baird, 1988; Mohr, Glover, & Ronning, 1984; Shirey, 1992; Shirey & Reynolds, 1988; Wade, 1992; Wade & Adams, 1990). For example, including an irrelevant picture with a text (i.e., a seductive illustration) is more harmful than providing no visualization with the text (e.g., Harp & Mayer, 1997). Furthermore, people are more likely to remember these seductive details than structurally critical information in the text (Garner, Alexander, Gillingham, Kulikowich, & Brown, 1991; Garner et al., 1992; Hidi & Anderson, 1992; Hidi & Baird, 1986). Thus, when the goal of a textbook is centered on students learning and remembering the main points within the text, presenting "interesting" pictures that offer no relevant support to the cognitive structure of the concept can actually be counterproductive.

By contrast, adding explanative summaries (i.e., material or illustrations that help the reader understand the structure of the explanation in the text) to scientific texts can help readers remember information and perform better on problem solving transfer tasks that require understanding of the material (Mayer, 1989; Mayer, Bove, Bryman, Mars, & Tapangco, 1996; Mayer, Steinhoff, Bower, & Mars, 1995). The aim of the current study was to expand on this research by examining whether relevant graphs that depict data already described in the text can be considered a type of explanative summary. If so, I would expect participants to demonstrate a benefit from this added visualization with regards to comprehension or memory of the text.

To evaluate the potential benefits of graphs, I conducted an experiment comparing comprehension of the pattern of data presented in a text when there was no visualization present, when there was an irrelevant "seductive" visualization present, and when there was a bar graph summarizing the data present. I selected and slightly modified an excerpt of text (and graph) from an actual psychology textbook (Goldstein, 2008), in which the data or findings for a scientific study about experience-dependent plasticity were explained (see Appendix E). Specifically, the text described data from a study by Gauthier, Tarr, Anderson, Skudlarski, and Gore (1999), in which participants were trained to view imaginary figures called "Greebles." Prior to the training, they were shown pictures of "Greebles" and faces, and only the faces activated the fusiform face area (FFA). Following training, both "Greebles" and faces activated the FFA. To understand the study and its conclusions, therefore, the participants would have to understand a complex 2-way interaction. In the current experiment (Experiment 1), participants first read the material and viewed the visualization, if present. As the focus of Experiment 1 was on the comprehension of complex data presented in textbook excerpts, participants then immediately answered questions about the data that was described.

A second goal of the present study was to investigate the effect of need for cognition (NFC; Cacioppo & Petty, 1982) on both understanding the data described in the text in general, as well as to investigate whether NFC interacted with the inclusion of graphs or seductive pictures in comprehending the information. In general, individuals higher on NFC comprehend text better (Dai & Wang, 2006). But how does NFC interact with the use of graphs in texts? It is possible that individuals with high NFC read the text with more attention or care and thus do not require a summary graph. Therefore, individuals with low NFC may benefit more from the inclusion of a graph than those with high NFC. In contrast, it is possible that individuals with high NFC are interested in learning from both the graph and the text and thus benefit more from a graph than those with low NFC.

Though seductive visualizations served primarily as a control condition in this study, it is also possible to consider how NFC interacts with susceptibility to seductive visualizations. Previous research on individual susceptibility to seductive details has found that individuals with low working memory capacity are more affected by the inclusion of seductive details than high working memory capacity individuals (Sanchez & Wiley, 2006). Likewise, individuals high in NFC may exert relatively more effort to comprehending text and ignoring irrelevant information.

Experiment 1

Method

Participants. Seventeen students (*M* = 18.41 years old; 14 women) from the University of Michigan Psychology Subject Pool completed the study in the laboratory, and received course credit for their participation. An additional 150 adult individuals (*M* = 34.77 years old; 67 women) participated in the study online via Amazon Mechanical Turk (MTurk). MTurk participants were compensated with $1.00 per approximately ten minutes of participation, as is standard procedure in our lab for studies using this online system. Most studies pay a much lower rate, so this higher rate of compensation was meant to further motivate participants. Although MTurk participants tend to be more diverse than typical American university samples, there is evidence to suggest that data collected with MTurk are at least as reliable as those collected in the lab (e.g., Buhrmester, Kwang, & Gosling, 2011). In addition, there were no significant differences in average performance in the laboratory and on MTurk. Therefore, the data from these two populations were combined for analyses. Three participants were excluded due to incorrect answers on questions intended to assess whether or not participants were attending to the questions, one participant was excluded due to incomplete or missing data, and three participants were excluded on the basis of having a task completion time of less than four minutes, or less than two standard deviations from the mean task completion time. This resulted in a final total of 160 participants (*M* = 33.51 years old; 80 women). The research protocol was approved by the University of Michigan Institutional Review Board, and all participants provided written informed consent.

Materials. The current experiment was conducted using Qualtrics (Qualtrics, Provo, UT) for easy online testing both in the laboratory and on Amazon MTurk. As it involved reading and comprehension questions, the experiment was self-paced such that participants progressed through the online task without any timing restrictions other than an automatic timing out of the webpage if not completed in less than one hour.

I chose to use a slightly modified excerpt of text (and graph) from an actual psychology textbook (Goldstein, 2008), in which the data or findings for a scientific study about experience-dependent plasticity were described (see Appendix E). This was a between-subjects design, such that participants were randomly assigned to one of three conditions. The excerpt was modified both in an attempt to slightly simplify the data set (to allow for a somewhat simpler graph) and to correspond to the three different conditions. In one condition, the text describing the study findings was presented by itself, with no visualization. In a second condition, participants read the same brief text presented with an irrelevant picture of a girl working at a computer. In a third condition, participants read the same brief text presented with a relevant bar graph that corresponded to the data described in the text.

Participants were tested on their comprehension immediately, such that there was no delay between the reading and the comprehension questions for that reading. The comprehension test included a single free-response question in which subjects were asked to briefly describe the main findings of the study in their own words, a multiple-choice question asking subjects to identify which bar graph correctly depicted the study findings, and a multiple-choice question asking subjects to identify which line graph correctly depicted the study findings. The inclusion of the line graph question was intended to examine comprehension differences as a function of graph format and to capture potential transfer of understanding of the data to a graph type that even those in the text with graph condition would not have previously viewed. Those who completed the study in the laboratory also completed a fourth question, an open-ended question in which they were asked to draw a graph that represented the expected results for a different variable based on what they knew of the study findings they read about. This question was intended as an additional transfer test of participants' comprehension of the findings, as they were asked to extrapolate based on the information presented in the textbook excerpt. However, this question was not included in the analyses as there were too few participants who completed this additional question.

All participants also completed the Need for Cognition (NFC; Cacioppo et al., 1996) scale. The NFC scale is an 18-item measure for which higher scores indicate a greater tendency to engage in and enjoy thinking (see Appendix C). Participants decided how characteristic of themselves each statement was, using a Likert scale ranging from 1 ("Does not describe me at all") to 5 ("Describes me perfectly"). Some items were reverse scored, and overall scores were obtained by summing responses to all of the items.

Procedure. All participants, including those who participated in the laboratory, completed the study online, via Qualtrics. Participants were instructed to carefully read a textbook excerpt about a scientific study, as they would be asked to answer some questions about the reading later. All participants first read a short textbook excerpt introducing the research study about experience-dependent plasticity. Following this brief excerpt, participants were presented with a second page of the text that described the study data, and this second page contained only the text, the text with an irrelevant picture, or the text with a relevant graph. After participants read the two pages of textbook material, they were asked to complete some comprehension questions about the data set discussed in the text, the NFC scale, and some demographic questions.

Results

The free response question was coded by three independent raters according to the coding scheme listed in Appendix F, such that responses were categorized according to what participants described about the textbook excerpt they read (e.g., study methods, study data or findings, general conclusions from the study). To assess the inter-rater reliability between the three raters, Fleiss' kappa was calculated with the use of an online kappa calculator (Geertzen, 2012). Inter-rater agreement for the data set following exclusions was moderate, with a kappa of .603. Select cases of disagreement were resolved either by using the code agreed upon by two of the three raters or, in select cases of no agreement among all three raters, by using the finalized coding of an independent, more experienced fourth rater. Because I was most interested in comparing correct descriptions of the excerpt's study data to all other response types, and because not all response categories occurred for all conditions, for the sake of analyses I combined the codes for correct descriptions of methods, correct descriptions of general conclusions, incorrect descriptions of the study data, and responses unrelated to the excerpt into a single response category.

There was no statistically significant association between condition and response type, $X^2(2, N = 160) = 1.47$, $p = .480$. Thus, format of the textbook excerpt does not seem to significantly affect the likelihood of a participant responding with a correct description of the study data or findings as opposed to a description of another kind. It is interesting to note that in general (i.e., across conditions) there were proportionately less correct descriptions of the study data (n = 62) than responses of some other type (n = 98), most of which were descriptions of the study's general conclusions (n = 78). This would perhaps suggest that most participants understood the main conclusions drawn based on the study findings even if they did not fully comprehend what these findings or data actually were, although it is possible that participants explained the conclusions rather than the actual data themselves due to misunderstanding the wording of the free response question.

Means of recognition accuracy for each condition (i.e., text only, text with irrelevant picture, text with graph) and question type (i.e., multiple choice line graph or bar graph question) are presented in Table 2.1. Based on the literature, I expected that presenting an irrelevant picture with the text would lead to worse performance than presenting the text by itself. I also expected that presenting a relevant graph with the text would be better in comparison to no visualization. Furthermore, I expected that, if participants were actually looking at the included visualization, a relevant graph presented with the text would result in much improved comprehension or memory for the text compared to an irrelevant picture. To look at these effects of condition, as well as the influence of individual differences (i.e., NFC) on comprehension, a between-subjects ANOVA was conducted with NFC as a covariate (see Table 2.2). However, contrary to expectations, there was no significant effect of condition (i.e., text only, text with irrelevant picture, text with graph) on overall accuracy for the multiple-choice questions, $F(4,310) = .910$, $p = .459$, Wilks' $\Lambda = .977$. Interestingly, accuracy was lowest for the text only condition and highest for the text with irrelevant picture condition, with accuracy for the text with graph condition falling in-between, though these differences were not significant. There was also no significant effect of condition on accuracy for the individual multiple-choice questions, as $F(2,154) = .07$, $p = .933$ for the bar graph multiple-choice question and $F(2,154) = .73$, $p = .485$ for the line graph multiple-choice question.

Need for cognition was significantly associated with overall accuracy for the multiple-choice comprehension questions, $F(2,153) = 7.88$, $p = .001$, such that individuals who enjoy more difficult thinking were more accurate in their responses to the multiple-choice questions. This was also true for each of the multiple-choice questions individually, as $F(1,154) = 12.14$, $p = .001$ for accuracy on the bar graph multiple-choice question and $F(1,154) = 7.64$, $p = .006$ for accuracy on the line graph multiple-choice question. These results indicate that although condition may not influence immediate comprehension for textbook reading, dispositional factors such as NFC certainly are influential for comprehension of complex data in textbook readings. There was no significant interaction between NFC and condition for overall multiple-choice accuracy ($F(4,306) = .44$, $p = .780$, Wilks' $\Lambda = .989$), nor was there a significant interaction between NFC and condition for either the bar graph multiple-choice question ($F(2,154) = .17$, $p = .843$) or the line graph multiple-choice question ($F(2,154) = .67$, $p =$

.512) individually. These findings suggest that although NFC mediates comprehension of textbook readings, higher or lower NFC does not benefit performance in this experiment for one particular condition more than another condition.

Accuracy on the two multiple-choice questions, bar and line graph, were significantly correlated with each other ($r = .31$, $p < .001$), which suggests that participants who understood the data well enough to recognize the correct graphical depiction of the data comprehended the excerpt well enough to do so regardless of graph type. Higher accuracy on the two multiple-choice questions combined was associated with a greater likelihood of correctly describing the excerpt's study data ($r = -.25$, $p = .002$), as was higher accuracy on the bar graph question ($r = -.20$, $p = .013$) alone and the line graph question ($r = -.20$, $p = .010$) alone. This makes sense given that those who did not understand the study data well enough to describe them in their own words would likely have a difficult time coming up with a correct graphical representation of the study data. Moreover, NFC was significantly correlated with accuracy on the bar graph multiple-choice question ($r = .28$, $p < .001$), the line graph multiple-choice question ($r = .23$, $p = .004$), and both of the multiple-choice questions combined ($r = .31$, $p < .001$). Thus, the more participants enjoy difficult thinking, the more accurate they were on the multiple-choice questions. These findings indicate that attitude towards effort, or dispositional factors such as enjoyment of difficult thinking, plays an important role in comprehension of textbook reading.

Discussion

Format of the textbook excerpt did not influence the likelihood of a participant to respond with a correct description of the study data or findings as opposed to a description of another kind. Most participants understood the main conclusions drawn based on the study findings, even if they did not fully comprehend what these findings or data actually were. Although no significant differences in accuracy were found between textbook excerpt formats, a clear impact of individual differences was found. Individuals with a higher need for cognition, or greater enjoyment of difficult thinking, were more accurate in identifying the bar and line graphs that correctly depicted the study's data in the excerpt. However, there was no evidence to support the interaction of NFC with the inclusion of graphs or seductive pictures in comprehending the information presented. One possible alternative explanation is that differences in cognitive capacity may underlie the relationship between NFC and performance. Future research should differentiate between dispositional factors and cognitive factors.

The statistically non-significant differences in accuracy between conditions are perhaps not so surprising, as some of the findings regarding seductive details indicate that seductive details such as irrelevant pictures at best afford no advantage over text alone and at worst are detrimental for performance compared to text alone. Although there was no clear detriment observed from presenting an irrelevant picture with the textbook excerpt in the current experiment, there was also no advantage from the inclusion of such a seductive detail. These results are therefore still consistent with the seductive details literature. With regards to the inclusion of a relevant graph, perhaps improved comprehension did not occur for this condition in comparison to the others because participants either did not use the graph or participants did try to use the graph but did not understand the graph or find it helpful. Additional research would be necessary to determine why the inclusion of relevant graphs are no better than reading the text alone or reading the text with irrelevant pictures. Maybe the relevant graph does not act as an explanative summary, as misunderstanding the graph would not help readers understand the structure or relationships within the data described in the text. If readers are bad at graph comprehension and thus graphs are not useful as explanative summaries, then perhaps in this case a relevant graph actually serves as more of a seductive detail or irrelevant and disruptive information for the reader.

Another potential explanation of the results is that the expected differences in accuracy between conditions, particularly for the inclusion of a relevant graph, are not clearly observable with an immediate test, but rather would be more apparent with a longer delay period between the reading of the excerpt and the comprehension test items. This would be consistent with findings in the learning and desirable difficulties literature. Perhaps varying conditions of the textbook excerpt do not matter for an immediate test, as the information read in the text is still active within memory, whereas a comprehension test based on long-term memory may be more susceptible to differences in processing of the reading due to the excerpt format. Thus, I would predict that the advantage of a graph, if it serves as an explanatory summary, may be greater after a one-week delay since conditions that affect learning, like the testing effect, have bigger impact at delay than with immediate testing. In fact, with the testing effect, at immediate test performance is better for the study condition, but with the delayed test performance is better for those with repeated testing (Roediger & Karpicke, 2006). Although the effects of seductive details and explanative summaries or illustrations have certainly been found within tasks that immediately follow the reading of an excerpt, perhaps such differences would be more pronounced in long-term memory. Therefore, additional research should determine whether this is the reason for the findings in Experiment 1.

Table 2.1

Means for Recognition Accuracy by Condition and Question Type

Condition	Question Type			
	Line Graph	**Bar Graph**	**Overall**	**N**
Text Only	.740 (.054)	.599 (.060)	.670 (.045)	57
Text with Irrelevant Picture	.843 (.059)	.733 (.066)	.788 (.050)	48
Text with Graph	.766 (.055)	.699 (.061)	.733 (.046)	55
Overall	.783 (.032)	.677 (.036)	.730 (.027)	160

Note. Values enclosed in parentheses represent standard errors. "Overall" values indicate values collapsed across condition or question type.

Table 2.2

Between-Subjects ANOVA of Recognition Accuracy by Condition with Need for Cognition (NFC) as a Covariate

Source	Accuracy	*df*	*F*	Partial η^2	*p*
NFC	Bar Graph	1	12.14**	.073	.001
	Line Graph	1	7.64**	.047	.006
Condition	Bar Graph	2	.070	.001	.933
	Line Graph	2	.726	.009	.485
Condition x NFC	Bar Graph	2	.171	.002	.843
	Line Graph	2	.673	.009	.512
Error	Bar Graph	154	(.207)		
	Line Graph	154	(.165)		

Note. ANOVA = analysis of variance. Values enclosed in parentheses represent mean square errors. *$p < .05$. **$p < .01$.

CHAPTER 3:
GRAPH COMPREHENSION IN IMMEDIATE AND LONG-TERM MEMORY TASKS

Introduction

Often, students are presented with graphs representing complex data with the expectation that they are able to comprehend the main points of the data set such that they could explain the data in their own words, and that they will be able to remember this information to draw from it later. This is evidenced by the frequent inclusion of graphs in textbooks, which clearly highlights the assumption that students comprehend and use such information. However, students are not particularly good at interpreting graphs, as seen both in the graph comprehension literature and in Experiment 1. As seen in Experiment 1, students may not fully understand complex data presented textually, even with the addition of a relevant graphical representation of the data. This leads to the question of what people are actually doing when interpreting multivariate graphs, which was the aim of Experiment 2. Do students come away from a graph with a clear understanding of the data set, such that they can explain the relationships within the graph?

Another question is whether students are able to identify the important information or relationships in a complex graph and understand them well enough to remember this information later from memory. If the goal of presenting data in graphs is to communicate critical concepts or research findings or to provide supporting scaffolding for textually presented information, then determining whether students grasp and remember the conclusions to be drawn from these graphs is extremely important. This question was the goal of Experiment 3. Additionally, there is some reason to believe that legends may add visual difficulty to graphs that would be beneficial or advantageous for task performance, particularly for long-term memory.

Therefore, in the next several experiments, I aimed to determine how well students identify main effects presented in line graphs in realistic tasks that involve describing and interpreting presented data in an open-ended context or remembering important aspects of a data set. I was also interested in potential differences between graph formats (i.e., labels versus legends) on these various graph comprehension tasks. Once again, in each of these experiments I also examined the role of individual differences on task performance and whether certain individual characteristics lend themselves to greater benefit from certain graph formats.

Experiment 2

Introduction

The goal of the current experiment was to examine what students actually identify as important information when presented with complex multivariate graphs. An open-ended graph description task would perhaps provide a better idea for what graphical relationships students identify and report as important compared to the more commonly used fact-retrieval task, in which students are asked a pointed question about a particular relationship presented in the graph. Because students are not directed to attend to one specific relationship in the graph in an open-ended task, and because each graph in the task contains a total of seven potential relationships (i.e., three main effects, three 2-way interactions, and one 3-way interaction) that could be described, this task may allow students to better indicate the different types of information that they are attending to in complex multivariate graphs.

Thus, in Experiment 2, I addressed students' ability to identify main effects and interactions in multivariate graphs within an open-ended context. I also investigated the influence of graph format and individual differences on task performance. I predicted that students would report a relatively fair proportion of the relationships in the data (i.e., at least 50%) given the open-ended and self-paced format of the task. I also hypothesized that students would report more main effects than interactions. However, I expected that students would report more complex relationships or interactions for graphs containing legends than graphs containing labels, because I thought that students may be more likely to identify such relationships in the data due to the built-in organization of the legend and additional processing required by these graphs. Students with increased graph skills and WM capacity were expected to correctly report more relationships in the data than students with low graph skills and WM capacity, and increased WM span was predicted to be especially important for graphs with legends compared to graphs with labels. Increased NFC, open-mindedness, and cognitive reflection were hypothesized to relate to correct identification of proportionately more relationships, particularly for graphs containing legends, compared to lower scores on these dispositional measures.

Method

Participants. Sixty-three individuals volunteered to participate in this experiment for course credit or for payment at the rate of $10 per hour. Two of these subjects were excluded from the data set for not completing the study (n = 1) or for leaving some of the test materials blank (n = 1), resulting in a total of 61 participants (*M* = 19.61 years; 19 women). Participants consisted of University of Michigan undergraduates from both the University of Michigan Psychology Subject Pool and the Ann Arbor community. Research protocols were approved by the University of Michigan Institutional Review Board, and all participants provided written informed consent.

Materials.

Graph Tutorial. Participants first completed a graph tutorial program run online using Qualtrics (Qualtrics, Provo, UT), which walked them through progressively more difficult graphs and open-ended questions relating to these graphs. For some example screenshots of the tutorial, see Figure 3.1. The concepts of main effects and interactions were defined in the tutorial. The tutorial also explained how to use a mental averaging procedure to answer questions about main effects relating to 2x2x2 line graphs (graphs containing 3 independent variables) via “static builds.” Static builds in the context of this tutorial are simply still frames that lay out the steps of the mental averaging process, one at a time, and highlight important or relevant pieces of the graph at each step (e.g. using color to highlight relevant lines or stars to mark averages). Finally, the tutorial provided participants with several practice questions. This tutorial was set up such that participants could type in their open-ended responses to each example.

Open-ended Graph Description Task. The open-ended graph description task was a paper task consisting of six graphs, three with labels and three with legends (see Figure 3.2 for examples). Graphs with labels in one version of the task had legends in a second version of the task, and vice versa. Graphs were black and white with some visual cues to differentiate between the lines (i.e., solid and dotted lines, circle and square end-points). Graph order was randomized for each participant. All graphs contained three independent variables (2x2x2 graphs), such that any description of the data could potentially include three main effects, three 2-way interactions, and one 3-way interaction. Participants were instructed to respond to information about various scenarios that depict information about a psychological study and data from the study presented graphically. They were told to imagine that they were trying to convey the information presented to them to someone who has little knowledge about the topic, and that their goal was to convey the main points from the scenario and the graph in a way that the person would fully understand without having to see the graph. Participants were also instructed that the scenarios and graphs presented would be fairly complex and that different people might highlight different information; thus, there are no right or wrong answers, and we are interested in what they think is important information to communicate about the data. Participants were requested to write about 2-5 sentences per graph, and it was estimated that the task would take them approximately 25 minutes. Participants were also provided with three examples of scenarios with corresponding graphs, along with sample answers for each data set that would be considered reasonable potential responses.

Individual difference measures. Participants completed a battery of individual difference measures, including the Edinburgh Handedness Inventory (Oldfield, 1971), Unusual Uses Task (Guilford, 1967), Cognitive Reflection Test (CRT; Frederick, 2005), Actively Open-minded Thinking Scale (AOT; Stanovich & West, 1997, 2007), Need for Cognition Scale (NFC; Cacioppo, Petty, Feinstein, & Jarvis, 1996), automated Symmetry Span task

(SSPAN; Unsworth, Heitz, Schrock, & Engle, 2005), and Graph Literacy Scale (Galesic & Garcia-Retamero, 2011).

Edinburgh Handedness Inventory. In this measure, participants indicated which hand(s) they would use for each task listed (Oldfield, 1971). As this task was used as a filler task and was not included in the analyses, it will not be discussed further with regards to scoring or analyses.

Unusual Uses Task. This task is a creativity measure in which participants are asked to generate as many possible uses for a common item (e.g. brick, bucket) as they can within two minutes (Guilford, 1967). As this task was used as a filler task and was not included in the analyses, it will not be discussed further with regards to scoring or analyses.

Cognitive Reflection Test. The CRT (Frederick, 2005) is a 3-item measure of an individual's ability to suppress an intuitive, automatic, or spontaneous incorrect response in order to come up with a more reflective and deliberative correct answer (see Appendix D). Scores were calculated by summing the total number of correct responses.

Actively Open-minded Thinking Scale. The AOT scale (Stanovich & West, 1997, 2007) consisted of 41 items (see Appendix B). Participants were instructed to select a response that best indicated their opinion for each item, using a Likert scale ranging from 1 ("strongly disagree") to 6 ("strongly agree"). Scores were computed by summing the responses to the questions. Some items were reverse scored, such that higher scores on the AOT indicate a greater tendency for open-minded thinking and cognitive flexibility, while lower scores indicate cognitive rigidity and resistance to belief change.

Need for Cognition Scale. This was the same measure as was used in Experiment 1. The NFC scale (Cacioppo et al., 1996) is an 18-item measure for which higher scores indicate a greater tendency to engage in and enjoy thinking (see Appendix C). Participants decided how characteristic of themselves each statement was, using a Likert scale ranging from 1 ("Does not describe me at all") to 5 ("Describes me perfectly"). Some items were reverse scored, and overall scores were obtained by summing responses to all of the items.

Symmetry Span Task. Participants also completed a computerized automated SSPAN task (Unsworth et al., 2005), a working memory span measure in which participants judged whether pictures were symmetrical while also trying to recall the location of squares on the screen in the correct sequential order (see Figure 3.3). This program was run using E-Prime 2.0 (Psychology Software Tools, Pittsburgh, PA). There were three practice sections prior to the actual trials: (1) practice on the storage task only (i.e., participants were presented with sequences of red squares that appeared within a 4x4 matrix and recalled and clicked on the locations of squares in the correct order on the grid); (2) practice on only the processing task (i.e., determining whether pictures made by filling in squares on an 8x8 matrix were symmetrical about the vertical axis); and (3) interleaved processing and storage tasks (i.e., each symmetry question was followed by a 650 ms presentation of a square, and participants indicated the locations of the squares in the correct sequential order at the end of a set). There were a total of 12 experimental trials, as there were three trials of each set-size with list length ranging from two to five. There was an individualized time limit for both the practice and actual trials of the interleaved task that was based on an individual's performance in the processing task only practice portion (i.e., individual's mean plus 2.5 standard deviations). Because the task is automated, a random combination of trials and list lengths was generated for each participant, and items to be recalled were distinct from the processing task. Feedback on accuracy for both the storage and processing tasks was presented at the end of each trial.

The program automatically calculates five scores: (1) the absolute load score, or the sum of all trials in which all items were recalled in the correct serial order; (2) the partial load score, or the sum of items recalled in the correct serial position regardless of whether the entire trial was recalled correctly; (3) processing errors, or the total number of errors made on the processing task; (4) speed errors, or the number of processing problems that were unanswered within the time limit; and (5) accuracy errors, or the number of processing problems answered incorrectly. I used the partial load score for all of the analyses as research indicates that partial-credit scoring is better than absolute scoring for complex span tasks (i.e., operation span, reading span, symmetry span) with regards to psychometric properties such as test-retest reliability, internal consistencies, and convergent validity (Redick et al., 2012). Furthermore, partial scoring captures additional variance that would not be captured with absolute scoring.

Graph Literacy Scale. This graph test (Galesic & Garcia-Retamero, 2011; see Appendix A) is a 13-item measure that assesses the three main graphical comprehension skills described by Friel et al. (2001): (1) the basic skill of reading the data or finding specific information in a graph; (2) the intermediate skill of finding relationships in the data presented in a graph; and (3) the advanced skill of making inferences and predictions based on the data. This scale also covers some of the most frequently used types of graphs, including line graphs, bar graphs, pie charts, and icon arrays. Scores were calculated by summing the total number of correct responses.

Demographic Questionnaire. The Demographic Questionnaire (see Appendix G) contains questions about gender, age, handedness, race, ethnicity, highest level of completed education, and their major in school. Participants are also asked about their familiarity with different types of graphs, how frequently they use graphs or tables, whether they prefer graphs or tables, how many math and statistics courses they have taken, their ACT or math SAT score, whether they consider themselves to be a math or science person, how confident they are in their scientific reasoning skills, and whether they are comfortable with numbers and graphs.

Exit Survey. Participants completed a brief Exit Survey at the end of the session (see Appendix H), consisting of five questions pertaining to potential strategies used in the study, what they thought was difficult in the study, their graph preferences, and what they thought was the purpose of the study.

Procedure. Participants first completed the online graph tutorial on the computer. This was followed by the open-ended graph description task. Next, participants completed a battery of individual difference measures, starting with the Edinburgh Handedness Inventory, followed by the Unusual Uses Task, the CRT, the AOT scale, the NFC questionnaire, the automated SSPAN, and the Graph Literacy Scale. Finally, participants filled out a demographic questionnaire as well as an exit survey prior to debriefing at the conclusion of the experiment. Participants completed the study in approximately 1.5 to 2 hours.

Results and Discussion

Open-Ended Graph Description Task. Participants' responses on the open-ended graph description task were coded according to the scheme found in Appendix I for each individual graph. First, responses were categorized by accuracy (correct or incorrect). Then responses were grouped into one of the following categories: description, or a description of the study related to the vignette or variables studied but that did not address any relationships in the data; main effect of X, or main effect of the variable on the x-axis; main effect of line, or main effect of the variable for which lines were differentiated by solid and dotted lines; main effect of circle/square, or main effect of the variable for which lines were differentiated by circle and square end-points; full 2-way interaction of X and line, or interaction between the variable on the x-axis and the variable for which lines were differentiated by solid and dotted lines; full 2-way interaction of X and circle/square, or interaction between the variable on the x-axis and the variable for which lines were differentiated by circle and square end-points; full 2-way interaction of line and circle/square, or interaction between the variable for which lines were differentiated by solid and dotted lines and the variable for which lines were differentiated by circle and square end-points; partial 2-way interactions, or responses that attempted to describe the relationship between two variables in the graph but that only described one part of the relationship (e.g., mentioning what was happening with one variable in relation to another but not vice versa); 3-way interaction, or interaction between all three variables in the graph; and partial 3-way interaction, or responses that attempted to describe the relationship between all three variables but only described part of the relationship. These partial 3-way interactions often tended to be descriptions of a single line in the graph. For partial 2-way interactions, the number of partial interactions reported (i.e., 1 to 3 per graph) was recorded.

One trained individual coded all of the participants' responses. A second rater coded the responses of 20% of the sample (data from a randomly selected 12 participants). The overall percent agreement between the two raters was 94.67%, with an "almost perfect"

Cohen's kappa coefficient of .84. Percent agreement for correct responses was 93% (with a substantial Cohen's kappa of .83), while percent agreement for incorrect responses was 98.59%. However, it is important to note that because there were very few cases of incorrect responses (only three), the kappa statistic would not be informative in this context (i.e., almost all of the agreement was that there were no incorrect responses) and was therefore not calculated for incorrect responses. Percent agreement for correct responses about main effects was 90.14% (with a substantial Cohen's kappa of 0.80), and the percent agreement for correct responses about interactions was 93.90% (with a substantial Cohen's kappa of 0.71). In the select cases of disagreement, the coding of the second more experienced individual was used for analyses.

Because there were very few incorrect responses made on the open-ended graph description task, the analyses focus on correct responses only. Additionally, all analyses were computed using proportions calculated for each aforementioned category of answer type. Thus, each proportion reflects the mean number of written statements provided by subjects divided by the total potential statements possible to provide for that particular category of answer type. For example, each 2x2x2 graph contains three possible main effects, which multiplied by six graphs in the task yields 18 total possible main effects that participants could mention in their responses on the task. A participant's proportion of main effects would therefore be the number of main effects they correctly describe divided by 18.

The mean proportion for correct responses collapsed across main effects and interactions was 0.19 (SE = .007), which is extremely low. Thus, overall, students report relatively very few main effects and interactions compared to what they could report given the amount and complexity of the relationships presented in the graphs. Students did report significantly more main effects than interactions of any type (2-way or 3-way, full or partial; M = .09, SE = .006), $t(60) = 10.50$, $p < .001$. Yet, the mean proportion of total correct main effects reported was 0.46 (SE = .031), which is less than 50% of the total main effects that students could have reported from the presented graphs. Interestingly, there were no significant differences between the mean proportions of reported main effects for main effects of the variable on the x-axis (M = .46, SE = .032), main effects of the variable indicated by solid or dotted lines (M = .46, SE = .036), and main effects of the variable indicated by circle or square end-points (M = .46, SE = .042), $F(2, 59) = .003$, $p = .997$, which suggests that the specific main effects reported by students were not attributable to the way in which those main effects were presented in the graphs. In other words, students were just as likely to correctly report main effects for each of the three variables of the multivariate data.

A series of paired t-tests were conducted to check for differences between proportions for graphs with labels and graphs with legends for the various categories of possible responses, but none of them were statistically significant (see Table 3.1). This suggests that, contrary to expectations, there was no effect of graph format (labels versus legends) in the open-ended graph description task. This was somewhat surprising, although upon further review of the task there are a few potential explanations for this finding. One explanation is that perhaps there is not a big enough difference between the stimuli in that the placement of the legends in these graphs is not very far removed from the location of the labels, and this may be why no effect of graph format was observed. Another, and perhaps more likely, explanation is that maybe graph format matters less when the task is predominately self-paced as well as open-ended. Additionally, it is possible that no differences in graph format were observed because the coding scheme was too fine-grained. Because there were many categories of responses, some categories had rather small proportions of responses compared to others. Therefore, future research could use a broader coding scheme to try to capture differences between graph formats that were unobserved with the current coding scheme.

Individual Differences. For means for each of the individual difference measures, please refer to Table 3.2. To determine the relationships between individual difference measures and task performance, I computed Pearson product-moment correlation coefficients (see Tables 3.3 and 3.4). Please note that one additional subject was excluded from the correlational analyses due to not completing any of the individual difference measures. Another four subjects were excluded from correlational analyses due to the individual difference measures being completed out of order. Also, one subject was excluded from correlations regarding the Graph Literacy Scale due to missing data on that one measure, and two subjects were excluded from correlations regarding the SSPAN task due to missing data on that measure. All correlations reported were significant at the $p < 0.05$ level unless stated otherwise.

Higher graph literacy scores were significantly associated with more open-mindedness and higher CRT scores. Higher working memory span was also correlated with higher CRT scores, while greater need for cognition was associated with increased open-mindedness and higher CRT scores. The overall proportion of correctly reported relationships increased with increasing graph literacy ($r = .24$, $p = .078$), as did the overall proportion of relationships described for graphs with labels ($r = .25$, $p = .064$). Higher WM span was significantly correlated with both the overall proportion of responses and the proportion of responses for graphs with legends, and was marginally correlated with the proportion of responses for graphs with labels ($r = .26$, $p = .056$). Increased CRT scores were significantly associated with a greater overall proportion of responses, and this was also true both for graphs with labels and graphs with legends.

Correlations for Main Effects. Students with higher graph literacy scores were marginally more likely to identify more main effects in general ($r = .24$, $p = .082$) and specifically more main effects for graphs with labels ($r = .23$, $p = .090$). Those with higher graph literacy were also more likely to identify main effects that corresponded to variables differentiated by circle or square end-points ($r = .26$, $p = .053$), and this was true for graphs with labels ($r = .25$, $p = .064$) but not for graphs with legends. Students with higher WM span tended to identify more main effects in general ($r = .23$, $p = .098$) and specifically more main effects for graphs with legends ($r = .24$, $p = .082$). Those with high WM span were also more likely to identify main effects that corresponded to variables differentiated by solid or dotted lines ($r = .27$, $p = .052$), and this was true for graphs with legends ($r = .24$, $p = .079$) but not for graphs with labels. More open-mindedness was associated with correct identification of more main effects that corresponded to variables on the x-axis ($r = .24$, $p = .076$), and this was especially the case when these graphs contained labels ($r = .32$).

Correlations for Interactions. Students with higher WM span identified more full 2-way interactions for legend graphs, especially when these interactions involved the variable on the x-axis and the variable shown using solid and dotted lines. Higher graph literacy was associated with more reports of full 2-way interactions between variables on the x-axis and variables shown using solid and dotted lines. Higher graph literacy was also associated with fewer reports of full 2-way interactions between variables on the x-axis and variables shown using circle and square end-points, especially when the graphs contained legends. Greater NFC was correlated with fewer descriptions about full 2-way interactions between variables shown using solid and dotted lines and variables shown using circle and square end-points in graphs with legends. Increased cognitive reflection was associated with more reports of full 2-way interactions between variables on the x-axis and variables shown using circle and square end-points, as well as with more reports of partial 3-way interactions and partial 3-way interactions for graphs with labels. More open-mindedness was marginally associated with less identification of full 2-way interactions for legend graphs ($r = .27$, $p = .094$). Higher WM span was marginally negatively correlated with identification of full 2-way interactions between variables shown using solid and dotted lines and variables shown using circle and square end-points for graphs with labels ($r = .23$, $p = .097$). Finally, more reports of full 2-way interactions between variables shown using solid and dotted lines and variables shown using circle and square end-points were correlated with lower CRT scores ($r = -.24$, $p = .077$).

In sum, graph literacy and WM span both predicted the mean proportion of correct main effects reported in the open-ended graph description task, but attitude (e.g., open-mindedness) was also an important factor. As expected, higher WM span appears especially important for reporting proportionately more main effects and interactions for graphs that contained legends. Additional dispositional characteristics (e.g., NFC and cognitive reflection) were also relevant factors with regards to the proportion of interactions reported.

Experiment 3

Introduction

Experiment 3 was intended to determine how well students identify main effects in the context of a task involving immediate and long-term memory of important aspects of data presented in graphs. In the current experiment, students must identify main effects in an open-ended context before knowing what question may be asked. This is perhaps more difficult than looking up information in a graph, as is the case in many fact-retrieval tasks in the graph literature, and is also a more realistic scenario as students may not know specifically which effects to look for in a graph prior to viewing it and would need to be able to identify what is important information in the data set on their own.

Furthermore, much of the graph literature favors labels over legends, but many of the studies upon which this recommendation is based consist of immediate fact-retrieval tasks. According to the concept of desirable difficulties, introducing difficulties such as legends may not benefit individuals in the short-term, but could benefit them in the long-term. Thus, in Experiment 3, I also wanted to test whether graph format had a differential effect in a long-term memory task (i.e., whether legends may actually benefit graph comprehension in LTM, at least for some individuals). Students were expected to be more accurate in responding to graphs containing legends than graphs containing labels in the LTM task, but this difference was not expected in the immediate task. Again, I also examined the role of individual differences in graph comprehension in the current experiment. Greater familiarity with graphs and increased WM capacity were hypothesized to be associated with better task performance in both immediate and LTM tasks, as were increased NFC, open-mindedness, and cognitive reflection. WM capacity was especially expected to influence accuracy for graphs with legends as compared to graphs with labels.

Method

Participants. Seventy-one individuals volunteered to participate in this experiment for course credit or for payment at the rate of $10 per hour. Fifteen of these participants were excluded due to low task performance of less than 60% on the first task (n = 8), equipment failure (n = 1), or failure to complete the study session (n= 6), resulting in a total of 56 participants (M = 19.13 years; 26 women). Participants consisted of University of Michigan undergraduates from both the University of Michigan Psychology Subject Pool and the Ann Arbor community. Research protocols were approved by the University of Michigan Institutional Review Board, and all participants provided written informed consent.

Materials. Participants first completed a graph tutorial similar to the one used in Experiment 2. However, this version of the graph tutorial only described main effects and the mental averaging process and excluded explanations of interactions in order to best correspond to the following experimental tasks. In contrast to Experiment 2, the tutorial program was run on the computer using E-Prime 2.0 (Psychology Software Tools, Pittsburgh, PA) instead of Qualtrics, with only slight modifications to match the format of the tutorial with that of the Graph First Verification Task (e.g., graph was viewed prior to the true-false statement, responses were true-false rather than open-ended).

Because in this experiment I was interested in the effect of added visual difficulty (i.e., legends) and individual differences on both immediate and long-term memory for graphically presented data, I used two different computerized tasks, one to test immediate memory (i.e., Graph First Verification Task) and one to test long-term memory (LTM). The Graph First Verification Task (see Figure 3.4) included six 2x2x2 graphs per condition (i.e., labels and legends; see Figure 3.2 for examples) and involved true-false statements about potential main effects presented in the graphs (see Appendix J for example statements). Students first read a brief description of the data set, and then they viewed the graph for a fixed duration of one minute prior to viewing and responding to the true-false statement. There was only one true-false question per graph in the Graph First Verification Task, totaling 12 questions. A group of 24 true-false statements was divided into two groups of 12. Thus, half of the participants were presented with one group of 12 true-false statements in the Graph First Verification Task and the other half were presented with the second set of 12 true-false statements. Trial order was randomized for each participant, and graphs that appeared with labels for some subjects appeared with legends for other subjects (and vice versa).

The LTM task (see Figure 3.5) was expected by the participants, as they had been instructed during the Graph First Verification Task that they would be asked questions about the graphs at a later time, and therefore the LTM task was not a surprise memory test. This task did not include any graphs, but rather prompted subjects to recall the graph or data set associated with each study description. Subjects first read a description of the study (same description that appeared in the Graph First Verification Task) and then responded to a true-false statement. They were then asked to indicate whether they had clearly remembered the data set associated with that statement or if they had guessed when responding to that statement. There were two true-false statements per data set, one repeated from the Graph First Verification Task and one new (from the remaining set of 12 true-false questions unused in the Graph First Verification Task), totaling 24 questions. Participants were allotted a maximum of one minute for each statement, and the screen advanced to the strategy question (i.e. remember or guess) upon response. Trial order was randomized for each participant, both for the order of the graphs and the order of the true-false statements.

All individual difference measures were the same as those used in Experiment 2.

All computer programs were run using E-Prime 2.0. True and false responses in the graph tutorial, Graph First Verification Task, and LTM task were made using the "c" and "m" keys on the keyboard, which were labeled "T" and "F" respectively. "Remember" and "Guess" responses in the LTM task were also made using the "c" and "m" keys, respectively. In the SSPAN task, all responses were made using the mouse.

Procedure. Participants first completed the graph tutorial program on the computer. Next they completed the Graph First Verification Task. Students were instructed to pay close attention to the graphs, as they would be asked questions about them later. This was followed by approximately 20 minutes of individual difference measures (i.e., Edinburgh Handedness Inventory, Unusual Uses Task, CRT, AOT, NFC), after which participants completed the LTM task on the computer. Then subjects completed the remainder of the individual difference measures (i.e., SSPAN, Graph Literacy Scale), followed by the demographic questionnaire and exit survey. All participants were debriefed at the conclusion of the experiment. Participants completed the study in approximately 1.5 hours.

Results and Discussion

Graph First Verification Task. Overall accuracy on this task was 84%. To assess the effect of graph format (label or legend) on task accuracy and response time (RT), a 1x2 within-subjects ANOVA was conducted (see Table 3.5). All calculations of RT are based on median RTs that have been filtered for correct responses only. There was no significant effect of graph format on task accuracy ($F(1,55) = 0.21$, $p = 0.646$) in this immediate task. Accuracy for graphs with labels ($M = .85$, $SE = .017$) was very similar to accuracy for graphs with legends ($M = .84$, $SE = .021$). This finding suggests that both graph formats, labels and legends, are effective for comprehension within the short-term. Although I checked for an effect of graph format on RT, it is important to note that RT in the current task is not an informative measure because the current task measures RT when participants are viewing the true-false statements after a fixed graph encoding time. Thus, in the current experiment a difference in RT was not predicted, and indeed no significant effect of graph type on RT was found ($F(1,55) = 1.14$, $p = 0.290$).

Long-term Memory Task. For this analysis I computed accuracy on LTM trials as a function of correct comprehension on the Graph First Verification Task trials. The intuition was that these LTM trials would be the ones for which participants were more likely to have actually encoded the graph since they correctly responded to a question about the graph in the Graph First Verification Task. Based on only these trials, overall accuracy in the LTM task was 79.6%. To determine whether graph format (label or legend) had an effect on task accuracy and response time (RT), I conducted a repeated measures ANOVA (see Table 3.5). Contrary to expectations, there was no significant difference in accuracy between graph with labels ($M = .79$, $SE = .022$) and graphs with legends ($M = .80$, $SE = .019$) in the LTM task, $F(1, 55) = 0.25$, $p = .618$. In the LTM task, RT indicated how long it took participants to verify a true-false statement from memory (without viewing the graph again). A difference in RT between graph formats was not expected, and indeed no significant effect of graph format on RT was found (F(1, 55) = 0.30, p = .587).

These results suggest that introducing difficulties into a graph (i.e., legends) does not benefit LTM more than other formats (i.e., labels). However, perhaps these difficulties only benefit individuals who have the capacity to deal with the added difficulty and so these differences are not observed within the data set as a whole. To address this question, I conducted a mixed repeated measures ANOVA to examine the effect of working memory ability (high versus low; between subjects) and graph format (label versus legends; within subjects) on performance in the Graph First Verification Task and the LTM task. Working memory groups were calculated based on a median split of the data according to SSPAN partial load scores. For this analysis, all LTM task trials were included as I was interested in accuracy change from immediate to LTM. Results indicated a non-significant 3-way interaction (F(1, 54) = 1.43, p = .236), but results did indicate a trend in the predicted direction, such that only individuals with high WM were not disadvantaged from the inclusion of legends in the LTM task (see Figure 3.6). Those with low WM span demonstrated an expected decline in performance from immediate to LTM, but this difference in accuracy was more pronounced for graphs with legends. These individuals had a relatively small decline in accuracy for graphs with labels from the immediate task (M = .81, SE = .023) to the LTM task (M = .74, SE = .029), in comparison to the greater decline in accuracy for graphs with legends from the immediate task (M = .82, SE = .031) to the LTM task (M = .72, SE = .029). This is a different pattern of results than what is found in the high WM span group. These individuals demonstrate a slightly larger decline in performance from the immediate task to the LTM task when graphs contained labels (M = .89, SE = .022 and M = .80, SE = .028, respectively), compared to the smaller decline in performance across tasks for graphs that contained legends (M = .85, SE = .030 and M = .80, SE = .028, respectively).

However, it is important to note that some items in the LTM task were repeated from the Graph First Verification Task. Thus, it may be informative to examine repeated items (i.e., how well individuals remembered the answer to questions answered previously) separately from new items in the LTM task. For repeated items, this 3-way interaction was marginally significant ($F(1, 54) = 3.32$, $p = .074$), with a similar pattern of results observed for low and high WM span groups, as individuals in the low WM span group were more detrimentally affected by legends from immediate to LTM than individuals in the high WM group. This suggests that legends were more harmful for those who do not have the capacity to deal with the added visual difficulty, especially when tested on the same information again. This 3-way interaction was not statistically significant for new items in the LTM task, and the pattern of results observed for the low and high WM span groups were a little different. Although high WM individuals showed a similar pattern to that observed in the prior analyses, individuals with low WM showed an almost equal amount of decline from immediate to LTM in both graphs with labels and graphs with legends. Collectively, these interaction results suggest that although high WM span individuals may not benefit from difficulties such as legends in the long-term, they are generally not disadvantaged by them as are low WM span individuals.

Also of interest was the relationship between reported memory for the individual data sets in the LTM task and students' actual performance on the LTM task. To determine the effect of reported guessing or remembering as well as graph type on students' accuracy in the LTM task, a within-subjects repeated measures ANOVA was conducted. Overall, as was expected, students' accuracy on the LTM task was much higher for questions for which they reported that they clearly remembered the data ($M = .81$, $SE = .023$) compared to their accuracy for questions for which they reported guessing ($M = .62$, $SE = .029$), $F(1,46) = 35.66$, $p < .001$. However, there was no interaction of reported remembrance or guessing in the LTM task with graph type, $F(1,46) = .001$, $p = .978$. Based on the desirable difficulties literature, I had predicted that LTM accuracy would be higher for graphs with legends than for graphs with labels for items that students reported clearly remembering, whereas I expected similar accuracy for both label and legend graphs for questions on which students reported guessing. Yet, again consistent with the prior analyses, this finding suggests that graph type did not influence the effect of reported remembrance for LTM task questions on LTM task accuracy.

Individual Difference Measures. For means for each of the individual difference measures, please refer to Table 3.2. To determine the relationships between individual difference measures and task performance, I computed Pearson product-moment correlation coefficients (see Table 3.6). Please note that two subjects were missing graph literacy scores and thus were not included in the comparisons involving graph literacy. All correlations reported were significant at the $p < 0.05$ level unless stated otherwise.

Increased open-mindedness was correlated with increased NFC. Higher CRT scores were associated with higher graph literacy and increased WM span. Graph literacy and WM span were correlated, such that higher graph literacy was associated with increased WM span.

Individual Differences in the Graph Verification Task. Higher graph literacy predicted overall accuracy on the Graph Verification Task and accuracy for graph with legends. Higher WM span was marginally correlated with accuracy for graphs with labels ($r = .23$, $p = .096$). Increased open-mindedness was associated with better overall accuracy on the Graph Verification Task and was marginally associated with better accuracy for graphs with legends ($r = .26$, $p = .051$). Decreased NFC was marginally associated with better overall task accuracy ($r = -.24$, $p = .076$).

Individual Differences in the Long-term Memory Task. Correlational analyses indicated that graph literacy ($r = .39$, $p = .004$) and WM span ($r = .29$, $p = .032$) measures both predicted overall performance on the LTM task. Both higher graph literacy and higher WM span were also associated with increased accuracy on graphs with legends in the LTM task ($r = .44$, $p = .001$ and $r = .33$, $p = .012$, respectively). More open-minded individuals generally performed better on the LTM task than less open-minded individuals ($r = .27$, $p = .048$). Finally, higher scores on the CRT were marginally associated with better performance on the LTM task ($r = .25$, $p = .069$).

General Discussion

Experiment 2 demonstrated that although students made very few errors in describing multivariate graphs, they also reported only a small fraction of the total possible relationships (main effects and interactions) existing in the data given the complexity of the graphs. Although students did report primarily main effects rather than interactions of any type (2-way or 3-way, full or partial), even the mean proportion of total correct main effects reported was less than 50% of the total main effects that students could have reported from the presented graphs. Thus, even when students report main effects, they do not report *all* of them, although they are equally likely to report main effects for each of the three variable types in a graph (variables on the *x*-axis, variables indicated by solid or dotted lines, and variables indicated by circle or square end-points). These results suggest that students may not grasp or understand all of the relationships presented in multivariate data, even after some brief explanation of what kinds of relationships are present in multivariate data and how to look for them in a graph. Alternatively, perhaps students choose not to report more complex relationships like interactions either because they do not fully understand them or because they are unsure of their ability to correctly articulate them. Another potential possibility is that students are simply not motivated to report such complex graphical relationships.

Additionally, results of Experiment 2 indicate that, contrary to expectations, there was no effect of graph format (labels versus legends) on identification of main effects and interactions in the open-ended graph description task. One plausible explanation is that graph format matters less when the task is predominately self-paced as well as open-ended. Alternatively, it is possible that no differences in graph format were observed because the coding scheme was too fine-grained, and additional future analyses could use a broader coding scheme to try to capture differences between graph formats that were unobserved with the current coding scheme.

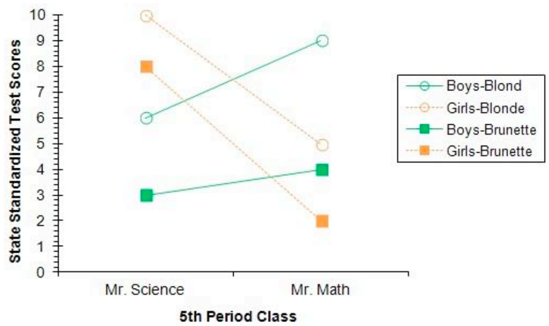
With regards to individual differences, results from Experiment 2 indicate that graph literacy and WM span were both highly predictive of the proportion of correct main effects and interactions students reported in an open-ended graph description task. Once again, dispositional characteristics, such as open-mindedness and NFC, were also influential with regards to task performance, both for identification of main effects and interactions.

In Experiment 3, no effect of graph format on accuracy was found in either the Graph First Verification Task or the LTM task. However, graph literacy and WM span were both generally predictive of accuracy in the Graph First Verification Task and LTM task. Individuals more highly skilled with graphs were more accurate in both immediate and LTM tasks, especially for graphs containing legends. This is consistent with the prediction that those more familiar with graphs would better know how to approach complex graphs or more easily learn from the included graph comprehension instructions. In contrast, WM span was more relevant for accuracy in the LTM task, especially for graphs containing legends. There are two potential explanations for this finding. One is that higher span individuals were better able to mentally transform the graphically presented data once it had been retrieved from LTM, in order to re-identify important relationships in the graph. Another explanation is that higher WM span individuals were better able to encode the relationships between variables in the first place, in the immediate task, because they perhaps were better able to keep track of the many variables while first interpreting the graph than low WM span individuals.

Thinking dispositions such as open-mindedness, NFC, and cognitive reflection also played a role in Experiment 3 task performance. Open-mindedness was influential for overall accuracy in both the immediate and LTM tasks. Individuals with lower NFC performed better in the immediate task than those with high NFC, perhaps because less cognitive effort was involved in remembering within the short-term. Meanwhile, higher cognitive reflection scores were associated with better overall accuracy in LTM, suggesting that perhaps individuals who take the time or put in the required effort to reach a more deliberate, correct answer better remember this information later.

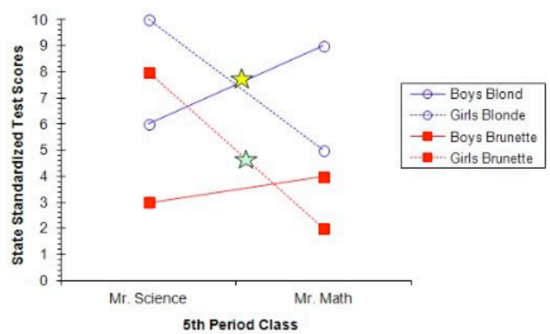
Moreover, a trend in the data suggests that "desirable" difficulties may not be beneficial for all individuals. Although perhaps not immediately apparent, individuals need to have the WM capacity to deal with such difficulties, or else added difficulty may actually be detrimental to task performance in the long-term. Additionally, increased open-mindedness was associated more specifically with increased accuracy on graphs containing legends in the immediate task. Thus, the potential benefits of desirable difficulties (e.g., legends) may be highly dependent both on an individual's ability to deal with these demands and on an individual's dispositions towards dealing with such demands.

Your description might include a statement that girls scored higher on the state standardized test if they were in Mr. Science's class than if they were in Mr. Math's class. However, boys actually did slightly better on the test if they were in Mr. Math's class.



This is a noticeable interaction in the graph since both of the lines for girls (in orange) are decreasing from left to right, while both of the lines for boys (in green) are increasing. Remember that an interaction occurs when the effect of an independent variable (i.e., sex) on the dependent variable (i.e., test score) is influenced by another independent variable (i.e., homeroom class).

You may have also noticed that one way to talk about the data in this graph is in relation to hair color (blond or brunette). As you can see in the graph below, blonds are the lines with circle end-points and brunettes are the lines with square end-points.



Clearly, the lines with circle end-points (highlighted in blue) are higher than the lines with square end-points (highlighted in red), which means that the blonds scored higher on the state standardized test than the brunettes.

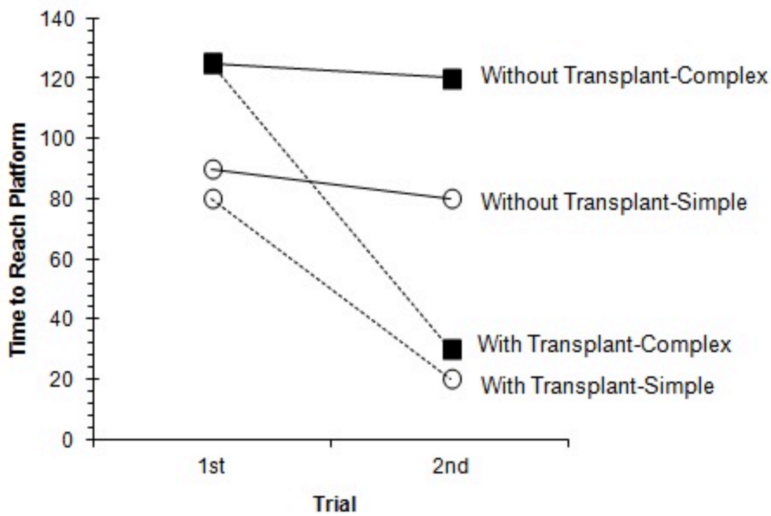
Please notice the stars located on the graph. These stars represent the averages between both sets of lines (the circle lines and square lines). Their location is the average of ALL FOUR POINTS for each set of lines. This is valid because in this graph, as in all the graphs, we are assuming that the same amount of data is represented by each of the four points.

As you can see in the graph, the star for the blue line averages (yellow star) is higher than the star for the red line averages (green star). Thus, the blonds scored higher than the brunettes on the state standardized test.

Therefore, a description of the graph could include a sentence about how, on average, blonds performed better on the state standardized test than the brunettes.

Figure 3.1. **Sample Screens of Graph Tutorial Explanations for Interactions and Main Effects**

(a)



(b)

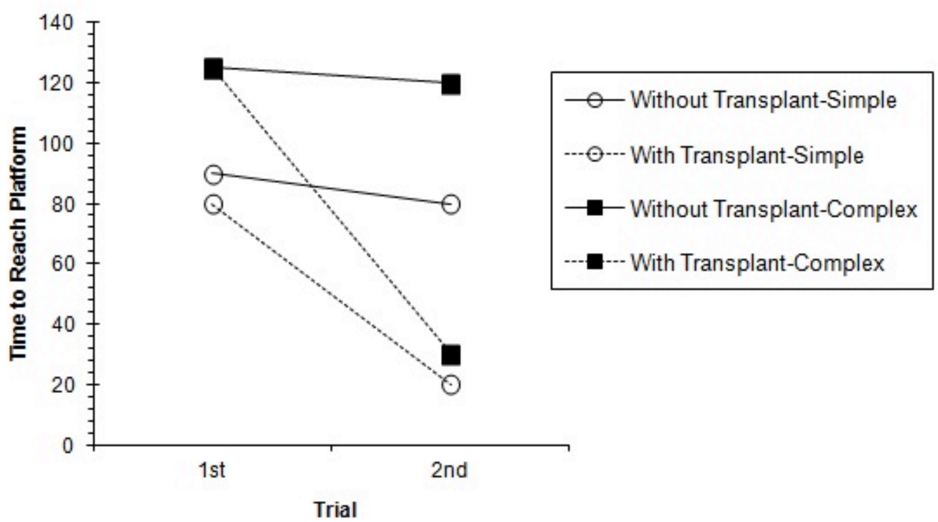


Figure 3.2. **Example 2x2x2 Line Graphs.** In this figure, (a) shows a sample graph with labels, while (b) shows a sample graph with a legend.

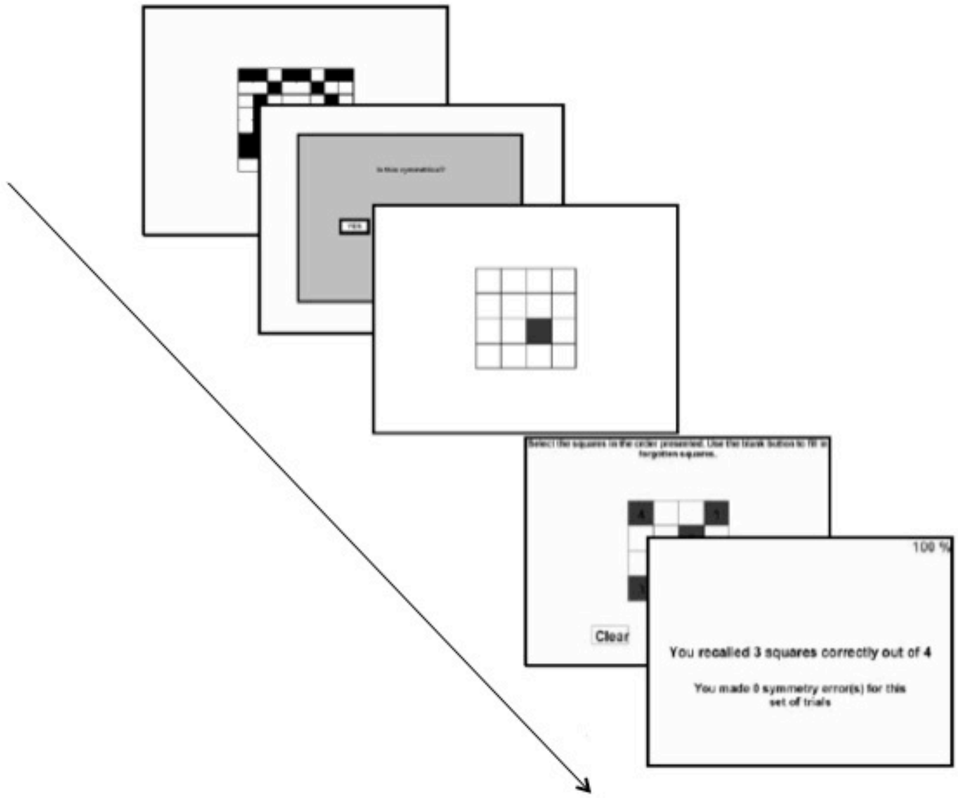


Figure 3.3. **Automated Symmetry Span Task Sample Trial Sequence**. This figure was modified from the one found in Redick et al. (2012).

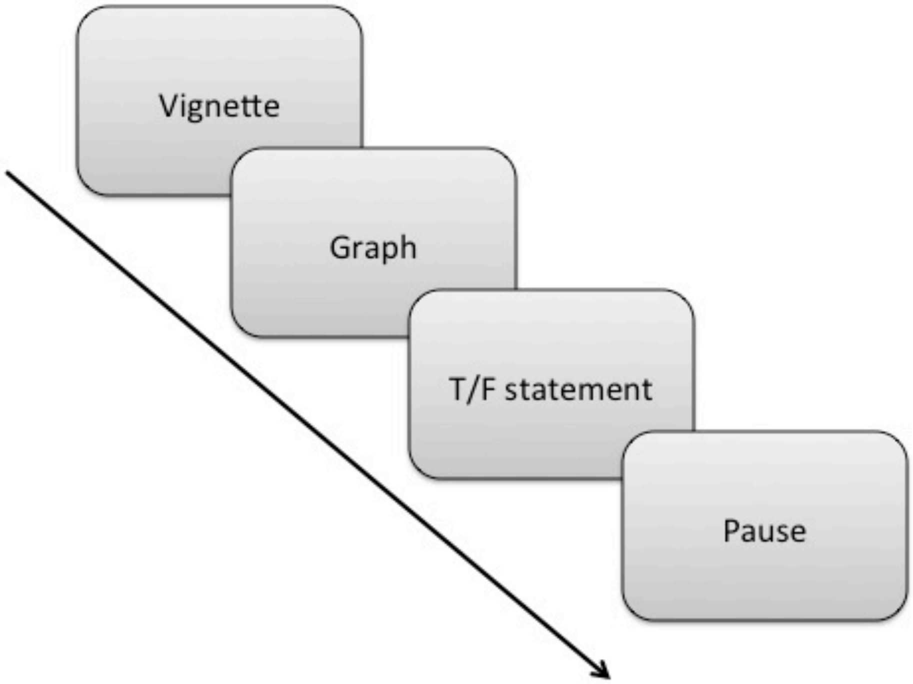


Figure 3.4. **Experiment 3 Graph First Verification Task Sample Trial Sequence**

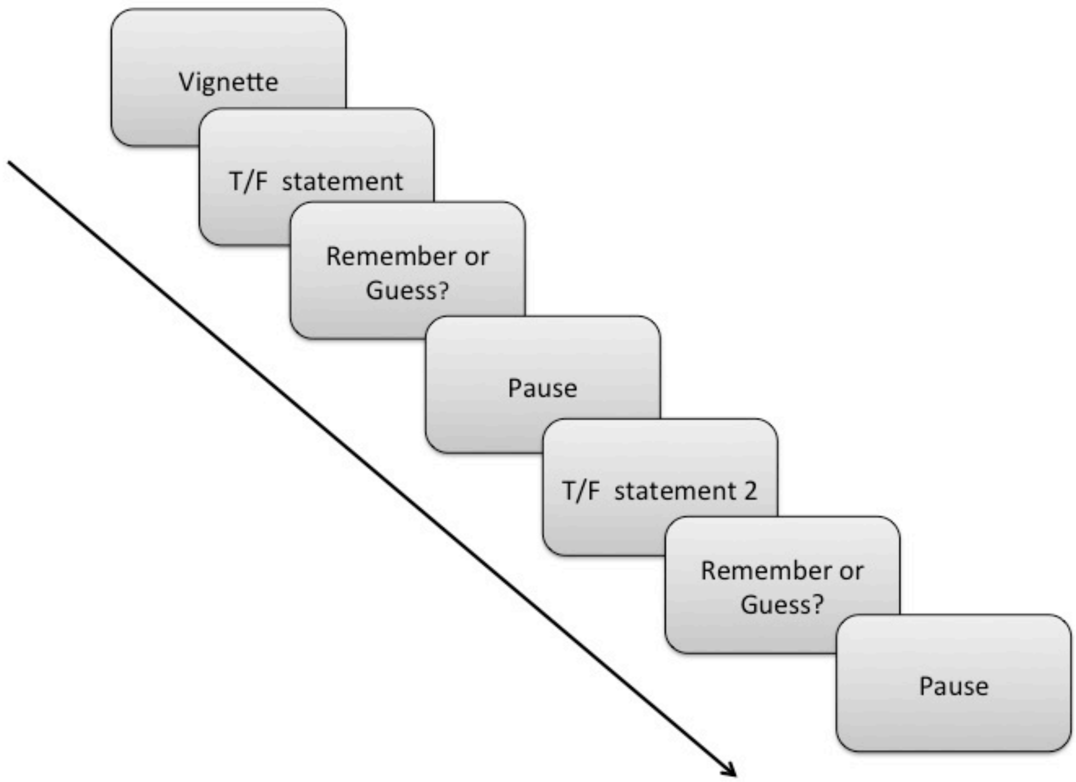
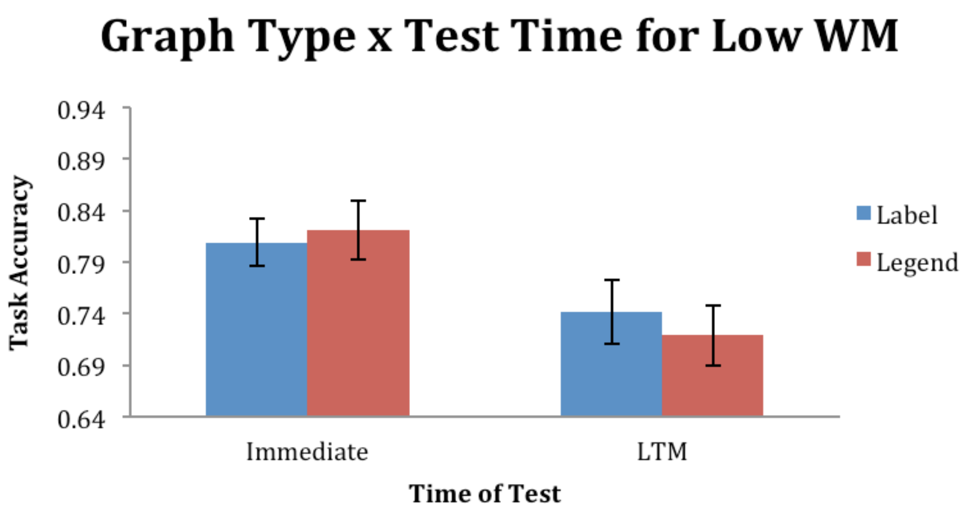


Figure 3.5. **Experiment 3 Long-Term Memory Task Sample Trial Sequence**



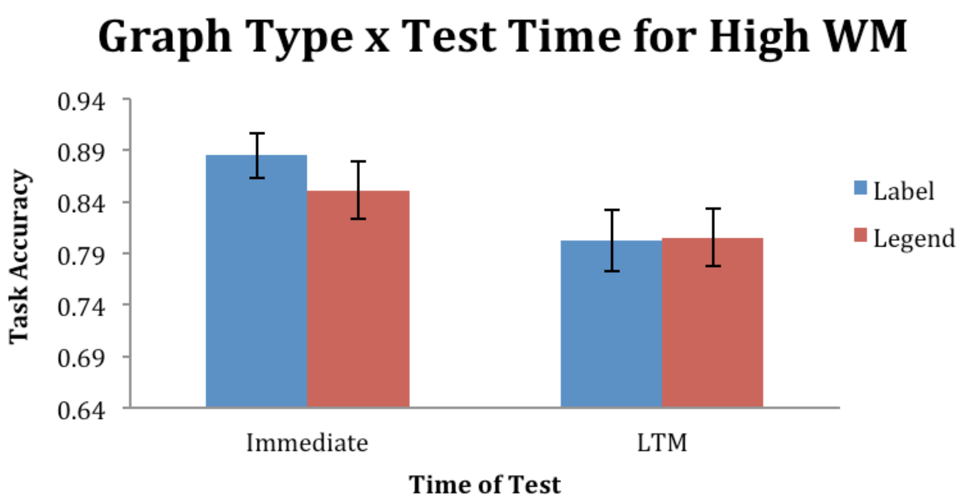


Figure 3.6. **Three-way Interaction between Working Memory Span, Time of Test, and Graph Type for Experiment 3**. Each graph depicts graph format (label versus legend) by time of test (immediate versus long-term memory or LTM). The top graph depicts the low working memory (WM) group, while the bottom graph depicts the high WM group. WM groups were determined by a median split.

Table 3.1

Paired Comparisons for Proportions of Correct Responses by Graph Type

	Graphs with Labels		Graphs with Legends			
	M	**SE**	**M**	**SE**	***t***	***p***
Overall	.197	.008	.190	.007	1.15	.255
All Main Effects	.470	.034	.450	.034	.755	.453
Main Effect of Variable on X-axis	.454	.038	.470	.035	-.476	.636
Main Effect of Single/Dotted Lines	.486	.042	.432	.044	1.18	.242
Main Effect of Circle/Square End-Points	.470	.048	.448	.048	.468	.641
All Interactions	.095	.007	.092	.008	.298	.767
All Full Interactions	.049	.007	.045	.006	.426	.672
Full 2-way Interactions	.060	.009	.058	.008	.148	.883
X-axis by Single/Dotted Line 2-way Interaction	.142	.021	.148	.021	-.173	.863
X-axis by Circle/Square End-Points 2-way Interaction	.016	.009	.016	.009	.000	1.00
Single/Dotted Line by Circle/Square End-Points 2-way Interaction	.022	.011	.011	.008	1.00	.321
All Partial Interactions	.141	.014	.140	.014	.075	.940
Partial 2-way Interactions	.124	.013	.124	.013	-.001	.999
Full 3-way Interactions	.016	.009	.006	.005	1.43	.159
Partial 3-way Interactions	.191	.032	.186	.030	.155	.877

Note. None of these comparisons are statistically significant. Degrees of freedom (*df*) for all comparisons are 60.

Table 3.2

Means of Individual Difference Measures for Experiments 2 and 3

	Graph Literacy	SSPAN	AOT	NFC	CRT
Experiment 2	11.73 (1.28)	28.56 (7.04)	176.23 (16.16)	60.59 (11.82)	1.45 (1.11)
Experiment 3	11.52 (1.45)	30.48 (7.22)	177.14 (17.46)	62.82 (10.92)	1.30 (1.14)

Note. Values in parentheses indicate standard deviations. For Experiment 2, N = 56 for all measures except for the Graph Literacy Scale (n = 55) and the SSPAN (n = 54). For Experiment 3, N = 56 for all measures except for the Graph Literacy Scale (n = 54).

Table 3.3

Correlations between Individual Difference Measures and Task Performance for Experiment 2

	Graph Literacy	SSPAN	AOT	NFC	CRT
Overall Proportion	.240†	.327*	-.030	.082	.363**
Overall Proportion for Graphs with Labels	.251†	.262†	.124	.153	.337*
Overall Proportion for Graphs with Legends	.174	.329*	-.191	-.014	.309*
Proportion of Main Effects	.236†	.228†	-.023	.010	.148
Proportion of Main Effects for Graphs with Labels	.231†	.182	.035	.011	.119
Proportion of Main Effects for Graphs with Legends	.204	.239†	-.078	.007	.154
Proportion of All Interactions	-.099	.033	-.001	.102	.254†
Proportion of All Interactions for Graphs with Labels	-.039	.028	.114	.195	.271*
Proportion of All Interactions for Graphs with Legends	-.118	.024	-.110	-.029	.135
Proportion of Full Interactions	.092	.151	-.174	-.105	.141
Proportion of Full Interactions for Graphs with Labels	.091	-.009	-.011	.034	.164
Proportion of Full Interactions for Graphs with Legends	.030	.243†	-.249†	-.198	.017
Proportion of Full 2-way Interactions	.047	.142	-.132	-.141	.116
Proportion of Full 2-way Interactions for Graphs with Labels	.035	-.065	.041	.015	.141
Proportion of Full 2-way Interactions for Graphs with Legends	.024	.270*	-.226†	-.209	.002
Proportion of Partial Interactions	-.143	-.027	.070	.153	.218
Proportion of Partial Interactions for Graphs with Labels	-.088	.036	.129	.193	.207
Proportion of Partial Interactions for Graphs with Legends	-.137	-.073	-.015	.051	.137
Proportion of Partial 2-way Interactions	-.188	-.089	.115	.097	.045
Proportion of Partial 2-way Interactions for Graphs with Labels	-.156	-.044	.148	.183	.026
Proportion of Partial 2-way Interactions for Graphs with Legends	-.129	-.088	.029	-.030	.041
Full 3-way Interactions	.137	.080	-.164	.041	.112
Full 3-way Interactions for Graphs with Labels	.177	.143	-.142	.062	.120
Full 3-way Interactions for Graphs with Legends	.029	-.050	-.153	-.007	.068
Partial 3-way Interactions	-.033	.054	-.011	.155	.330*
Partial 3-way Interactions for Graphs with Labels	.033	.113	.047	.117	.330*
Partial 3-way Interactions for Graphs with Legends	-.092	-.025	-.069	.140	.211
Graph Literacy	—	.029	.297*	.166	.276*
SSPAN		—	-.102	.048	.283*
AOT			—	.501*	.181
NFC				—	.460*
CRT					—

Note. *$p < .05$. **$p < .01$. †marginally significant ($p < .10$). All proportions listed are for correct responses only. Individual difference measures include Graph Literacy Scale scores, Symmetry Span partial load scores (SSPAN), Actively Open-Minded Thinking Scale scores (AOT), Need for Cognition Scale scores (NFC), and Cognitive Reflection Test scores (CRT).

Table 3.4

Additional Correlations between Individual Difference Measures and Task Performance for Experiment 2

	Graph Literacy	SSPAN	AOT	NFC	CRT
Proportion of Main Effects of Variable on X-axis	.117	.150	.239†	.085	.150
Proportion of Main Effects of Variable on X-axis for Graphs with Labels	.074	.130	.324*	.164	.073
Proportion of Main Effects of Variable on X-axis for Graphs with Legends	.136	.135	.093	-.018	.197
Proportion of Main Effects of Single/Dotted Lines	.195	.266†	-.108	-.130	.072
Proportion of Main Effects of Single/Dotted Lines for Graphs with Labels	.203	.218	-.128	-.202	.086
Proportion of Main Effects of Single/Dotted Lines for Graphs with Legends	.130	.241†	-.057	-.020	.038
Proportion of Main Effects of Circle/Square End-Points	.262†	.157	-.143	.069	.146
Proportion of Main Effects of Circle/Square End-Points for Graphs with Labels	.252†	.088	-.070	.073	.116
Proportion of Main Effects of Circle/Square End-Points for Graphs with Legends	.204	.185	-.180	.046	.138
Proportion of Full 2-way Interactions for X by Line	.270*	.214	-.037	-.051	.161
Proportion of Full 2-way Interactions for X by Line for Graphs with Labels	.110	-.018	.148	.035	.093
Proportion of Full 2-way Interactions for X by Line for Graphs with Legends	.253†	.313*	-.199	-.103	.125
Proportion of Full 2-way Interactions for X by Circle/Square	-.475**	.023	-.122	-.017	.122
Proportion of Full 2-way Interactions for X by Circle/Square for Graphs with Labels	-.200	.097	-.152	.062	.336*
Proportion of Full 2-way Interactions for X by Circle/Square for Graphs with Legends	-.452**	-.066	-.016	-.086	-.169
Proportion of Full 2-way Interactions for Line by Circle/Square	.005	-.185	-.130	-.245	-.238†
Proportion of Full 2-way Interactions for Line by Circle/Square for Graphs with Labels	.052	-.228†	-.068	-.100	-.169
Proportion of Full 2-way Interactions for Line by Circle/Square for Graphs with Legends	-.078	.028	-.137	-.306*	-.177

Note. *$p < .05$. **$p < .01$. †marginally significant ($p < .10$). All proportions listed are for correct responses only. Individual difference measures include Graph Literacy Scale scores, Symmetry Span partial load scores (SSPAN), Actively Open-Minded Thinking Scale scores (AOT), Need for Cognition Scale scores (NFC), and Cognitive Reflection Test scores (CRT).

Table 3.5

ANOVA of Task Accuracy and Response Time (RT) by Graph Type and Task

	Source	Measure	*df*	*F*	Partial η^2	*p*
Immediate Task	Graph Type	Accuracy	1	.213	.004	.646
		RT	1	1.14	.020	.290
	Error	Accuracy	55	(.019)		
		RT	55	(3219775.40)		
Long-Term Memory Task	Graph Type	Accuracy	1	.252	.005	.618
		RT	1	.299	.005	.587
	Error	Accuracy	55	(.015)		
		RT	55	(1438250.75)		

Note. ANOVA = analysis of variance. Values enclosed in parentheses represent mean square errors. *$p < .05$. **$p < .01$.

Table 3.6

Correlations between Individual Difference Measures and Graph First Verification Task Performance for Experiment 3

	Graph Literacy	SSPAN	AOT	NFC	CRT
Overall Immediate Graph Accuracy	.289*	.117	.280*	-.239†	.065
Immediate Label Graph Accuracy	.110	.225†	.142	-.262†	.010
Immediate Legend Graph Accuracy	.298*	-.020	.262†	-.114	.078
Graph Literacy	—	.392**	.155	-.097	.343*
SSPAN		—	.078	.032	.319*
AOT			—	.269*	.094
NFC				—	.122
CRT					—

Note. *$p < .05$. **$p < .01$. †marginally significant ($p < .10$). Individual difference measures include Graph Literacy Scale scores, Symmetry Span partial load scores (SSPAN), Actively Open-Minded Thinking Scale scores (AOT), Need for Cognition Scale scores (NFC), and Cognitive Reflection Test scores (CRT).

CHAPTER 4:

GRAPH COMPREHENSION INSTRUCTION

Introduction

As mentioned previously, students are not especially good at comprehending multivariate graphs and no explicit guidelines on how to teach comprehension of complex multivariate graphs currently exist, which makes it difficult for instructors to create or find effective instructional tools for interpretation of such data. This suggests the need for an instructional resource, such as a tutorial, that teachers could use to help instruct their students. Such a tutorial would explain how to identify and interpret important relationships within multivariate data presented graphically to help students learn and improve on their existing graph comprehension skills.

The prior two experiments indicated that, even with the completion of a graph tutorial prior to a graph comprehension task, students are not especially good at extracting main effects and interactions from complex multivariate data in an open-ended context, nor do they have excellent immediate or long-term memory for these important relationships depicted in graphs. Therefore, the goal of the current experiment was to determine the effectiveness of the tutorial I created as an instructional tool for students.

A general task-analysis approach was taken to develop the tutorial. Specifically, I identified the visual/cognitive transformations required to understand each main effect in a 2x2x2 graph. For each variable, participants are required to mentally compute the average across the other two variables for each value of that target variable. Thus, to compute the variable depicted by solid versus dotted lines, participants must first mentally compute the midpoint of each solid line and then mentally compute the average of these two midpoints. This average would be the overall value for the variable indicated by solid lines. Participants would then compute the overall value for the variable indicated by dotted lines using the same process, after which they would compare these two averages (overall mean for solid lines and overall mean for dotted lines) to determine the direction of the main effect, if one is present. In the tutorial, this mental averaging process was laid out in steps, one at a time, with important or relevant pieces of the graph highlighted at each step (e.g., using color to highlight relevant lines and stars to mark averages). This was accomplished using "static builds", or still frames of each step, which can be seen in Figure 4.1. For example, when highlighting which two lines would be mentally averaged to compute the overall average for boys (solid lines) and which two lines would be mentally averaged to compute the overall average for girls (dotted lines), the color orange was used to highlight the lines for girls and the color green was used to highlight the lines for boys. The use of color was intended to provide an added visual cue for grouping of the relevant information being compared in the example in the attempt to make the information provided in the tutorial easier to follow and comprehend. Stars were used to mark the estimated averages for boys (solid lines) and girls (dotted lines), to make the mental averaging concept more concrete and easily visible to participants. Color was also used for the stars, to help participants connect the appropriate averages to each level of the variable being compared (i.e., orange star for girls' average and green star for boys' average). After completing this mental averaging example containing "static builds", participants would then have to use the same mental averaging process to determine whether a main effect was present for each of the other two variables (i.e., the variable labeled on the *x*-axis and the variable indicated by circle and square end-points) in the graph.

Thus, in the tutorial students are walked through progressively more difficult graphs and questions relating to these graphs. When they reach the most difficult 2x2x2 graph, "static builds" are used to demonstrate the mental averaging process required to identify main effects in the sample graph. Finally, the tutorial provides participants with several practice questions.

Thus, in the next two experiments, I address the question of whether students are able to understand and interpret main effects presented in graphs in an immediate fact-retrieval task and whether they can be trained to identify and better comprehend such data using the tutorial I have created. Furthermore, I investigate the role of individual differences in task performance to determine whether individual differences would play a role both in students' existing skill in comprehending main effects and in the training of such complex data comprehension skills.

Experiment 4

Introduction

In Experiment 4, my aim was to determine how well students are able to identify main effects without explicit prior instruction or training on how to do so. This experiment would therefore provide a baseline for student performance, with which I could later compare performance on the same task for students who received additional instruction from the computerized tutorial (Experiment 5). Additionally, individual differences were evaluated as critical factors in graph comprehension.

Method

Participants. Thirty-four individuals volunteered to participate in this experiment for course credit or for payment at the rate of $10 per hour. Two of these participants were excluded due to low task performance of less than 60%, resulting in a total of 32 participants (M = 19.63 years; 19 women). Participants consisted of University of Michigan undergraduates from both the University of Michigan Psychology Subject Pool and the Ann Arbor community. Research protocols were approved by the University of Michigan Institutional Review Board, and all participants provided written informed consent.

Materials.

Question First Verification Task. Participants were provided with two practice questions prior to beginning the experimental trials. A trial began with a brief description about a scientific study, followed by a single true-false statement (see Appendix J for sample statements). Then a graph was presented and participants judged whether the statement they had just read was true or false while viewing the graph. A sample trial is illustrated in Figure 4.2. As in Experiment 3, each graph was a line graph depicting 2x2x2 data (see Figure 4.3 for examples). Graphs were black and white with some visual cues to differentiate between the lines (i.e., solid and dotted lines, circle and square end-points). Half of the graphs contained labels and half of the graphs contained legends. Participants were instructed to respond as quickly and as accurately as possible. Graphs were presented for a maximum of one minute, and the graphs terminated upon response. Then participants were given a second true-false statement corresponding to the same data set, followed by the presentation of the graph for a second time. Once again, participants judged whether the statement they had just read was true or false while viewing the graph. There were 12 such trials in the Question First Verification Task, totaling 24 true-false statements. These true-false questions were the same as the ones used in Experiment 3. Trial order was randomized for each participant, and graphs that appeared with labels for some subjects appeared with legends for other subjects (and vice versa).

It is important to note that the key difference between the immediate task in the current experiment and that of Experiment 3 is that in the Question First Verification Task in Experiment 3 students must identify main effects in an open-ended context before knowing what question may be asked, whereas in the current experimental task students receive the question prior to viewing the graph and thus can focus only on information pertaining to that individual question.

All individual difference measures were the same as the ones used in Experiments 2 and 3.

All computer programs were run using E-Prime 2.0 (Psychology Software Tools, Pittsburgh, PA). In the graph tutorial and Question First Verification Task, true and false responses were made using the “c” and “m” keys on the keyboard, which were labeled “T” and “F” respectively. In the SSPAN task, all responses were made using the mouse.

Procedure. Participants first completed the Question First Verification Task on the computer. Next, participants completed the same battery of individual measures as described in Experiment 2. Finally, participants completed a demographic questionnaire about themselves, as well as an exit survey about the study. All subjects were debriefed at the end of the experiment. The duration of the study was approximately one hour.

Results and Discussion

Question First Verification Task. Overall, task accuracy was an above chance 0.77. To assess the effect of graph format (label or legend) on task accuracy and response time (RT), a 1x2 within-subject ANOVA was conducted (see Table 4.1). All calculations of RT are based on median RTs that have been filtered for correct responses only. There was a significant main effect of graph type on both accuracy ($F(1,31) = 5.87$, $p = .021$) and RT ($F(1,31) = 26.11$, $p < .001$). Participants were significantly more accurate in responding to graphs with labels ($M = .81$, $SE = .023$) than graphs with legends ($M = .73$, $SE = .023$). This finding suggests that, as predicted, interpreting graphs with legends is more difficult than interpreting graphs with labels. As expected based on prior data, participants were also faster to respond to graphs with labels ($M = 8088.17$ ms, $SE = 928.38$) than to graphs with legends ($M = 11658.73$ ms, $SE = 783.30$).

Individual Differences. For means for each of the individual difference measures, please refer to Table 4.2. To determine the relationships between individual difference measures and task performance, I computed Pearson product-moment correlation coefficients (see Table 4.3). Please note that one additional subject was excluded from the correlational analyses due to prior familiarity with at least one of the individual difference measures and one subject was excluded from correlations regarding the AOT due to missing data for this measure. All correlations reported were significant at the $p < 0.05$ level unless stated otherwise.

Graph literacy was marginally correlated with overall task accuracy ($r = .33$, $p = .068$) and with accuracy on graphs with labels ($r = .35$, $p = .057$). Interestingly, there was no correlation between graph literacy and accuracy on graphs with legends. One possible explanation is that using legends requires specialized skills and even those with graph experience may not know how to approach interpretation of these kinds of graphs. Higher CRT scores were significantly correlated with higher WM span, higher graph literacy, and a greater NFC.

I then conducted a median split based on participants' SSPAN partial load scores to split the data into a low WM group (M = 22.36; n = 14) and a high WM group (M = 35.41; n = 17 for all measures except for the AOT, for which n = 16), to see if WM span had a differential effect on whether individual differences would affect task performance. For those with low WM capacity, open-mindedness was marginally correlated with overall task performance (r = .51, p = .064) and with accuracy for graphs with legends (r = .50, p = .070). For those with high WM capacity, graph literacy was marginally predictive of overall task performance (r = .42, p = .090) and significantly predictive of accuracy on graphs with labels (r = .59). Additionally, for the high WM group, higher scores on the CRT were marginally correlated with accuracy on graphs with labels (r = .45, p = .068). Therefore, dispositional factors such as open-mindedness appear to play a larger role in graph comprehension when individuals have less capacity to deal with difficulty.

Experiment 5

Introduction

As seen in Experiment 4, students who received no specialized instruction (i.e., no graph tutorial) were capable of interpreting relatively complex graphs with above chance accuracy. However, there was certainly room for improvement, as mean accuracy did not approach ceiling. Therefore, the goal of Experiment 5 was to determine whether the graph tutorial that I created is an effective instructional tool for the purpose of improving students' graph literacy skills. In the current experiment, students completed a graph tutorial prior to completion of the same tasks used in Experiment 4. Student performance in Experiment 5 is thus compared with student performance from Experiment 4 to determine the success of the current graph tutorial. Additionally, I investigated the impact of individual differences on instruction of graphical literacy.

Method

Participants. Sixty-six individuals volunteered to participate in this experiment for course credit or for payment at the rate of $10 per hour. Four of these participants were excluded due to low task performance of less than 60% (n = 2), failure to follow task instructions (n = 1), or failure to complete the study session (n= 1), resulting in a total of 62 participants (*M* = 19.24 years; 35 women). Participants consisted of University of Michigan undergraduates from both the University of Michigan Psychology Subject Pool and the Ann Arbor community. Research protocols were approved by the University of Michigan Institutional Review Board, and all participants provided written informed consent.

Materials. Participants first completed the same graph tutorial program on the computer that was used in Experiment 3, with only slight modifications to match the format of the tutorial with that of the Question First Verification Task (e.g., the true-false statement was viewed prior to the graph). For example screenshots of the tutorial see Figure 4.1. Thus, the tutorial walked students through progressively more difficult graphs and true-false questions relating to these graphs. The tutorial also explained how to use a mental averaging procedure to answer questions about main effects relating to 2x2x2 line graphs via "static builds." Static builds in the context of our tutorial are simply still frames that lay out the steps of the mental averaging process, one at a time, and highlight important or relevant pieces of the graph at each step (e.g. using color to highlight relevant lines or stars to mark averages). Finally, the tutorial provided participants with several practice questions.

The same Question First Verification Task used in Experiment 4 and the same individual difference measures used in Experiments 2-4 were used in Experiment 5. The instructions for the Question First Verification Task were very subtly changed to reflect the inclusion of the tutorial preceding it, but otherwise remained identical to the version used in Experiment 4.

All computer programs were run using E-Prime 2.0 (Psychology Software Tools, Pittsburgh, PA). In the graph tutorial and Question First Verification Task, true and false responses were made using the "c" and "m" keys on the keyboard, which were labeled "T" and "F" respectively. In the SSPAN task, all responses were made using the mouse.

Procedure. Participants first completed the graph tutorial program, followed by the Question First Verification Task on the computer. Next, participants completed a battery of individual difference measures, starting with the Edinburgh Handedness Inventory, followed by the Unusual Uses Task, the CRT, the AOT scale, the NFC scale, the automated SSPAN, and the Graph Literacy Scale. Finally, participants completed the demographic questionnaire about themselves as well as an exit survey about the study. All subjects were debriefed at the end of the experiment.

Results and Discussion

Question First Verification Task. Overall, task accuracy was 0.83. This is significantly higher than the task accuracy of 0.77 in Experiment 4 ($F(1,92) = 7.38$, $p = .008$), as determined by a mixed repeated measures 2x2 ANOVA of graph type (label or legend) and tutorial use (tutorial or no tutorial). Thus, completing the Question First Verification Task after the tutorial resulted in a significantly higher overall task accuracy than completing the same task without the tutorial. This suggests that my tutorial is an effective tool for teaching students how to identify main effects in these kinds of 2x2x2 line graphs. Alternatively, it is possible that the tutorial is increasing students' motivation for completing the task or their attention to the task rather than, or in addition to, improving students' graph comprehension skills.

To assess the effect of graph format (label or legend) on task accuracy and response time (RT) in the current experiment, a within-subjects ANOVA was conducted (see Table 4.1). All calculations of RT are based on median RTs that have been filtered for correct responses only. Consistent with prior research, participants were faster verifying a statement when viewing graphs with labels ($M = 7558.83$ ms, $SE = 464.42$ ms) than graphs with legends ($M = 9777.08$ ms, $SE = 469.83$ ms; $F(1,61) = 32.17$, $p < 0.001$). This also replicates the effect of graph type on RT found in Experiment 4. However, there was no difference in accuracy between graphs with labels ($M = 0.84$, $SE = 0.014$) and graphs with legends ($M = 0.82$, $SE = 0.018$; $F(1,61) = 0.83$, $p = 0.365$). This is in contrast to the significant difference in accuracy that occurred in Experiment 4, which would suggest that the inclusion of the tutorial in the current experiment might have somehow lessened the overall difficulty of the legend graphs. I conducted a mixed repeated measures 2x2 ANOVA of graph type (label or legend) and tutorial use (tutorial or no tutorial) to determine whether this interaction between graph type and tutorial use was significant. Results indicated a marginally significant interaction ($F(1,92) = 2.78$, p

= .099) between graph type and tutorial use. Thus, participants who did not complete the tutorial performed worse on both graph types in the task compared to those who did complete the tutorial, but this discrepancy in accuracy was especially notable for graphs with legends. One potential explanation for this difference in results between Experiments 4 and 5 is that the primary example in the graph tutorial that demonstrates to participants how to identify main effects within a line graph contains a legend.

A regression analysis was conducted to ascertain which of the various individual differences (i.e., graph literacy, WM span, open-mindedness, NFC) most impacted task accuracy and whether this differed between those who received additional instruction from the graph tutorial and those who did not. The CRT was not included in the model due to its limited range of scores and thus small amount of variance. For regression results see Table 4.4. However, because open-mindedness did not contribute to the regression model for either Experiment 4 or 5, a separate regression was run without the inclusion of open-mindedness in order to achieve the best possible fit of the model for the data (see Table 4.5). Results of this regression analysis suggest that when students receive no additional instruction, graph literacy is the only significant predictor of their task performance, $\beta = .389$, $t(26) = 2.10$, $p = .046$. Thus, those who are more knowledgeable about graphs will be more accurate in responding to true-false questions about main effects presented in the graphs. This is consistent with the graphical literacy literature, and is a rather intuitive finding. In contrast, for those students who do receive additional instruction from the graph tutorial, other individual differences emerge as significant predictors of task performance. It is extremely interesting that in this case knowledge about graphs is a marginally significant predictor ($\beta = .215$, $t(58) = 1.87$, $p = .066$), whereas WM capacity ($\beta = .256$, $t(58) = 2.20$, $p = .032$) and attitude towards difficult thinking ($\beta = .290$, $t(58) = 2.45$, $p = .017$) matter more for performance. This finding suggests that those with higher NFC or higher WM span will benefit more from instruction than those who do not enjoy difficult thinking or have lower WM capacity. Therefore, both WM capacity and attitude of the learner will impact the effectiveness of additional graph instruction. Given that WM span and NFC are correlated such that higher WM span is associated with higher NFC (see Table 4.6 and the correlational analyses that follow), perhaps those with lower WM capacity do not enjoy difficult thinking because it requires too much effort and they have less capacity to deal with overcoming challenges. Therefore, maybe they do not benefit as much from instruction because they do not engage with the material, are unable to keep track of all the relevant information, or simply find the task of interpreting complex multivariate graphs too effortful, hard, or overwhelming.

Individual Difference Measures. For means for each of the individual difference measures, please refer to Table 4.2. To determine the relationships between individual difference measures and task performance, I calculated Pearson product-moment correlation coefficients (see Table 4.6). Please note that one subject was excluded from correlations regarding the AOT due to missing data on that one measure. All correlations reported were significant at the $p < 0.05$ level unless stated otherwise.

Working memory capacity and graph literacy each predicted overall accuracy on the Question First Verification Task, as expected. WM capacity was more highly correlated with accuracy for graphs with labels than for graphs with legends, although this was not a significant difference ($t(59) = 0.62$, $p = 0.27$). Graph literacy was correlated with accuracy for graphs with legends, but not for graphs with labels. NFC and the CRT also both predicted task performance. Interestingly, NFC was more highly correlated with task accuracy in the legend condition than in the label condition, though this was not a significant difference ($t(59) = -0.16$, $p = 0.57$). Additionally, the CRT was correlated with performance in the label condition, but not the legend condition. WM capacity was also correlated with both the NFC and CRT measures. Performance on the CRT was correlated both with graph literacy and open-mindedness. Graph literacy was marginally correlated with open-mindedness ($r = 0.24$, $p = .066$) and NFC ($r = 0.22$, $p = .089$). As in Experiment 4, these results suggest that dispositional factors such as need for cognition and cognitive reflection play a substantial role in task performance, in addition to factors more related to knowledge or skill (i.e., graph literacy and WM span).

I then conducted a median split based on participants' WM partial load score to split the data into a low WM group ($M = 22.30$; n = 30) and a high WM group ($M = 34.22$; n = 32), to see if WM had a differential effect on whether these other individual differences would affect task performance. For those with low WM capacity, NFC was marginally correlated with overall task accuracy (r = 0.35, p = .059). Performance on the CRT was significantly correlated with graph literacy (r = 0.65) and with open-mindedness (r = 0.48). Graph literacy was only marginally correlated with open-mindedness (r = 0.35, p = .056). Meanwhile, for those with high WM capacity, overall task accuracy was predicted by graph literacy (r = 0.45), NFC (r = 0.39), open-mindedness (r = 0.37), and CRT score (r = 0.45). Accuracy on graphs with labels was correlated with WM capacity (r = 0.40), graph literacy (r = 0.35), and CRT score (r = 0.59), whereas accuracy on graphs with legends was correlated with graph literacy (r = 0.40), NFC (r = 0.38), and open-mindedness (r = 0.37). Performance on the CRT was also correlated with WM capacity (r = 0.36) and graph literacy (r = 0.54). In contrast to the pattern of results observed in Experiment 4, these results indicate that dispositional factors are important for both low and high WM span groups. However, in this case it seems that more dispositional factors are predictive of task performance for those with high WM span rather than low WM span.

General Discussion

Experiment 4 demonstrated that students who receive no specialized training are capable of interpreting relatively difficult graphs with above chance accuracy, although there is certainly room for improvement, as mean accuracy did not approach ceiling. Taken collectively, results from Experiments 4 and 5 indicate that students are faster to verify true-false statements in an immediate fact-retrieval task when graphs contain labels than when they contain legends, which is consistent with findings in the graph design literature. Moreover, in comparing Experiments 4 and 5, although individuals who received no specialized instruction were more accurate in responding to graphs with labels than graphs with legends, this difference in accuracy between graph formats was diminished with the use of a graph tutorial. This suggests that the graph tutorial was potentially an effective tool for teaching students how to deal with difficulties in graph comprehension. This also suggests that any potential differences in accuracy due to varying graph format may have been unobserved in Experiments 2 and 3 because of the inclusion of the tutorial. In other words, the tutorial may serve to negate possible advantages of labels over legends by better familiarizing students with varying graph formats and providing them with opportunities to practice interpreting such graphs.

With regards to individual differences, the general conclusion derived from Experiments 4 and 5 is that dispositional factors (e.g., open-mindedness, NFC) play a substantial role in graph comprehension, in addition to factors more related to knowledge and skills (e.g., graph literacy, WM span). It remains unclear as of yet whether dispositional factors play a larger role for low knowledge or lesser skilled individuals (i.e., low graph literacy or WM span) as compared to individuals with greater knowledge and skills (i.e., high graph literacy or WM span). However, it is apparent from these experiments that although familiarity with graphs is important for graph comprehension, WM capacity and attitude towards thinking hard are key factors in the effectiveness of instruction of graph comprehension skills. Specifically, students who do not enjoy effortful thinking are less likely to benefit from instruction, which suggests a need for educators to foster enjoyment of cognitive work in order for training of graphical skills to be effective.

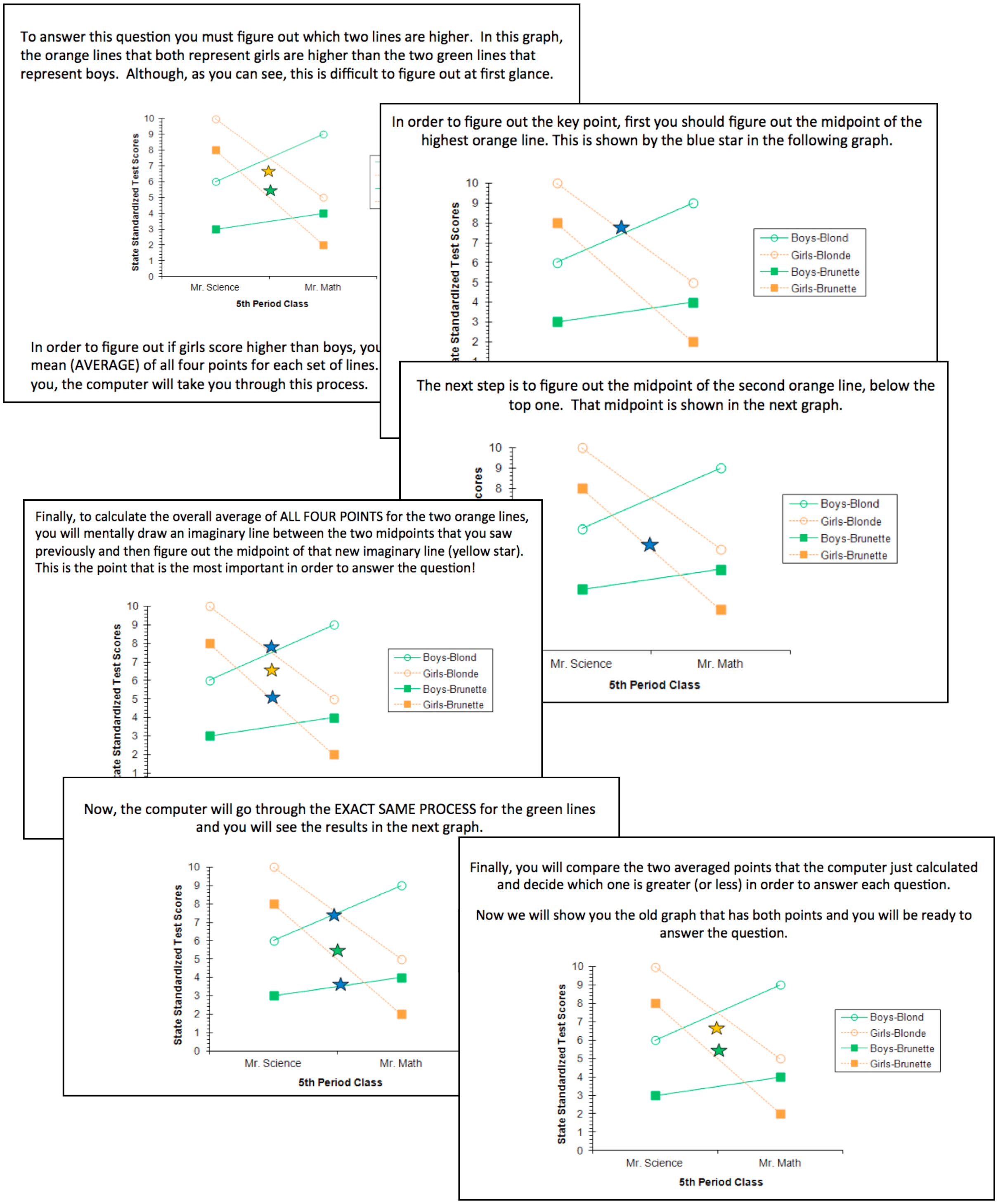


Figure 4.1. **Example of Graph Tutorial "Static Builds" for the Mental Averaging Process for Main Effects.** This example demonstrates the mental averaging process for the variable "Girls", indicated by the dotted lines (highlighted in orange), and "Boys", indicated by the solid lines (highlighted in green).

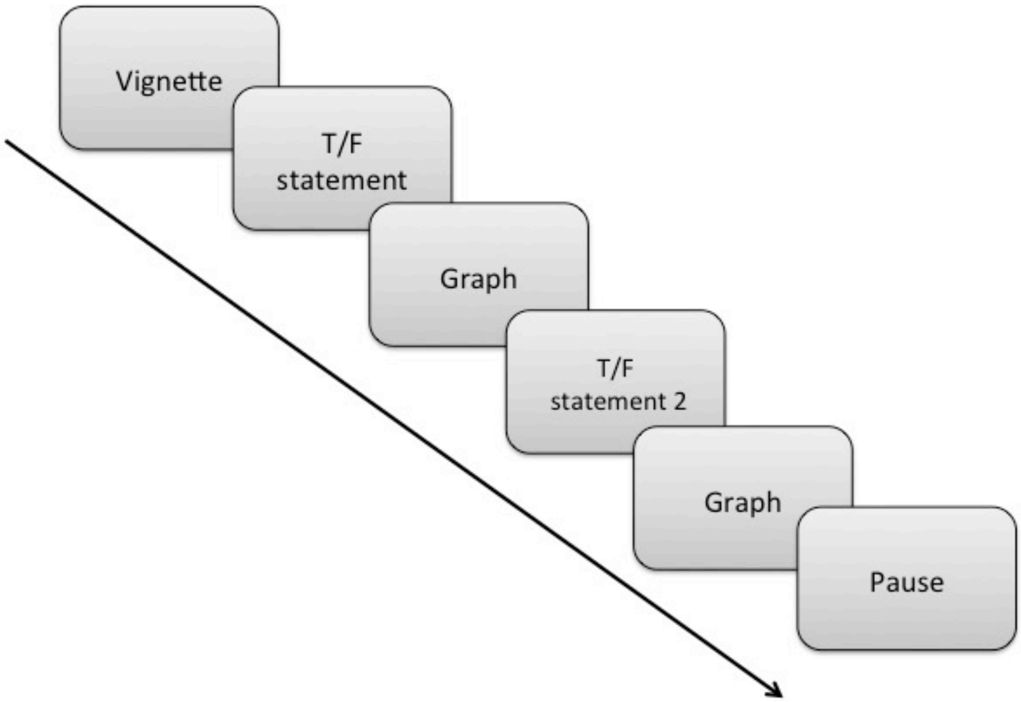
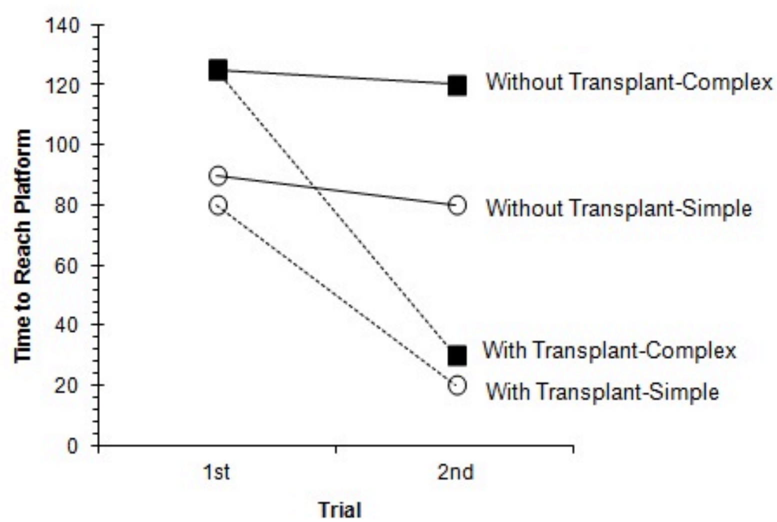


Figure 4.2. **Experiments 4 and 5 Question First Verification Task Sample Trial Sequence**

(a)



(b)

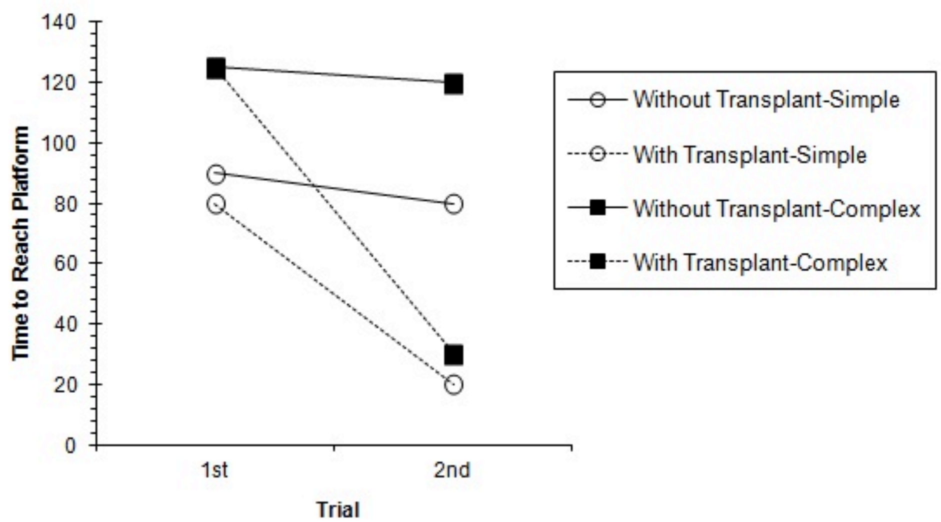


Figure 4.3. **Example 2x2x2 Line Graphs.** In this figure, (a) shows a sample graph with labels, while (b) shows a sample graph with a legend.

Table 4.1

ANOVA for Task Accuracy and RT by Graph Type (Label/Legend) and Experiment

Experiment	Source	Measure	*df*	*F*	Partial η^2	*p*
4	Graph Type	Accuracy	1	5.87*	.159	.021
		RT	1	26.11**	.457	.000
	Within-group Error	Accuracy	31	(.016)		
		RT	31	(7812742.51)		
5	Graph Type	Accuracy	1	.832	.013	.365
		RT	1	32.17**	.345	.000
	Within-group Error	Accuracy	61	(.011)		
		RT	61	(4741584.73)		

Note. ANOVA = analysis of variance. Values enclosed in parentheses represent mean square errors. $*p < .05$. $**p < .01$.

Table 4.2

Means of Individual Difference Measures for Experiments 2-5

	Graph Literacy	SSPAN	AOT	NFC	CRT
Experiment 2	11.73 (1.28)	28.56 (7.04)	176.23 (16.16)	60.59 (11.82)	1.45 (1.11)
Experiment 3	11.52 (1.45)	30.48 (7.22)	177.14 (17.46)	62.82 (10.92)	1.30 (1.14)
Experiment 4	11.77 (1.28)	29.52 (8.02)	180.93 (13.38)	65.42 (8.98)	1.52 (1.15)
Experiment 5	11.21 (1.54)	28.45 (7.88)	179.54 (21.29)	63.90 (12.50)	1.23 (1.10)

Note. Values enclosed in parentheses indicate standard deviations. For Experiment 2, N = 56 for all measures except for the Graph Literacy Scale (n = 55) and the SSPAN (n = 54). For Experiment 3, N = 56 for all measures except for the Graph Literacy Scale (n = 54). For Experiment 4, N = 31 for all measures except for the AOT (n = 30). For Experiment 5, N = 62 for all measures except for the AOT (n = 61).

Table 4.3

Correlations between Individual Difference Measures and Task Performance for Experiment 4

	Graph Literacy	SSPAN	AOT	NFC	CRT
Overall Graph Accuracy	.332†	.189	.266	-.152	.243
Label Graph Accuracy	.346†	.278	.280	-.138	.282
Legend Graph Accuracy	.155	.000	.123	-.094	.081
Graph Literacy	—	.102	.079	.257	.510**
SSPAN		—	-.125	.137	.641**
AOT			—	-.058	.053
NFC				—	.466**
CRT					—

Note. **p* < .05. ***p* < .01. †marginally significant ($p < .10$). Individual difference measures include Graph Literacy Scale scores, Symmetry Span partial load scores (SSPAN), Actively Open-Minded Thinking Scale scores (AOT), Need for Cognition Scale scores (NFC), and Cognitive Reflection Test scores (CRT).

Table 4.4

Regression Analyses for Experiment 4 versus Experiment 5 with All Individual Difference Measures

	Experiment 4			Experiment 5		
	B	*SE B*	*β*	*B*	*SE B*	*β*
WM Span	.002	.002	.195	.004	.002	.293*
Graph Literacy	.036	.019	.356†	.015	.008	.226†
NFC	-.003	.002	-.280	.002	.001	.268*
AOT	.002	.001	.246	.000	.001	-.019
R^2	.15			.24		
F	2.32†			5.60**		

Note. *p < .05. **p < .01. †marginally significant (p < .10). Factors included Working Memory (WM) span, Graph Literacy, Need for Cognition (NFC), and Actively Open-minded Thinking (AOT). The Cognitive Reflection Test (CRT) was excluded from the regression analyses due to its limited range and small variance.

Table 4.5

Regression Analyses for Experiment 4 versus Experiment 5 with Working Memory (WM) Span, Graph Literacy, and Need for Cognition (NFC)

	Experiment 4			Experiment 5		
	B	*SE B*	*β*	*B*	*SE B*	*β*
WM Span	.002	.002	.160	.003	.002	.256*
Graph Literacy	.040	.019	.389*	.015	.008	.215†
NFC	-.003	.002	-.299	.002	.001	.290*
R^2	.12			.23		
F	2.33†			7.23**		

Note. *$p < .05$. **$p < .01$. †marginally significant ($p < .10$).

Table 4.6

Correlations between Individual Difference Measures and Task Performance for Experiment 5

	Graph Literacy	SSPAN	AOT	NFC	CRT
Overall Graph Accuracy	.302*	.351**	.114	.404**	.310*
Label Graph Accuracy	.161	.338**	.004	.314*	.318*
Legend Graph Accuracy	.277*	.250*	.140	.337**	.194
Graph Literacy	—	.092	.237†	.218†	.594**
SSPAN		—	.076	.261*	.297*
AOT			—	.212	.303*
NFC				—	.165
CRT					—

Note. *$p < .05$. **$p < .01$. †marginally significant ($p < .10$). Individual difference measures include Graph Literacy Scale scores, Symmetry Span partial load scores (SSPAN), Actively Open-Minded Thinking Scale scores (AOT), Need for Cognition Scale scores (NFC), and Cognitive Reflection Test scores (CRT).

CHAPTER 5:

CONCLUSION

Summary of Findings

The current research was comprised of three main goals: (1) to determine how well people comprehend main effects and interactions in complex multivariate data presented graphically, and whether graph format plays a role (i.e., whether legends function as a desirable difficulty); (2) to determine whether students can be taught to better identify and understand main effects and interactions inherent in graphs of complex data sets, and what would comprise such an effective tutorial; and (3) to examine the role of individual differences in complex graph comprehension, as well as in the training of these skills.

Given the widespread usage of graphs across many media and the apparent assumption made by publishers of these media that people are capable readers of graphical information, a critical first question is whether people use information presented in graphs when reading textual information such as an article or textbook that already contains a summary of the data, and, if they do use these graphs, whether the graph is helpful. Results from Experiment 1 demonstrate that the format of textbook readings (i.e., text only, text with irrelevant seductive picture, text with relevant graph) does not affect immediate recognition accuracy for the presented study data, nor does it affect the likelihood of an individual to correctly describe the study data as opposed to describing something else from the textbook reading (e.g., study methods or general conclusions drawn from the study). Most individuals seemed to understand the main conclusions drawn based on the study findings even if they did not fully comprehend what the findings of the study actually were. These results were still consistent with the seductive details literature because although there was no clear detriment observed from presenting an irrelevant picture with the textbook excerpt, there was also no advantage from the inclusion of such a seductive detail. Future research would be necessary to determine why the inclusion of relevant graphs are no better than reading the text alone or reading the text with irrelevant pictures. Perhaps the relevant graph did not act as an intended explanative summary because readers are bad at complex graph comprehension and therefore the inclusion of the graph disrupted the processing of the data rather than help readers understand the structure or relationships within the data described in the text.

This lack of differences between textbook reading formats could also be attributed to the type of test. Perhaps these differences are not clearly observable with an immediate test, but would be more apparent with a longer delay period between the reading of the excerpt and the comprehension test items, which would be consistent with findings in the learning and desirable difficulties literature. I would predict that the advantage of a graph, if it serves as an explanatory summary, may be greater after a one-week delay since conditions that affect learning, like the testing effect, have bigger impact at delay than with immediate testing. In fact, with the testing effect, at immediate test performance is better for the study condition, but with the delayed test performance is better for those with repeated testing (Roediger & Karpicke, 2006).

In Experiment 2, students made very few errors in describing multivariate graphs, but they also reported only a small fraction of the total possible relationships (main effects and interactions) existing in the data given the graphs' complexity. Although students did report primarily main effects rather than interactions of any type, this mean proportion was still less than 50% of the total main effects that students could have reported from the presented graphs. Thus, even when students report main effects, they do not report *all* of them, although they are equally likely to report main effects for each of the three variables in a graph. This result contradicts the summarization by Shah and Hoeffner (2002) that line graphs are best for emphasizing *x*-*y* relationships, but perhaps this is because the tutorial included prior to the task and instructions for the task pointed out the existence of relationships in graphically presented data for variables not on the *x*-axis. Together, these results suggest that students may not understand all of the relationships presented in multivariate graphs, even after some brief explanation of what kinds of relationships are present in multivariate data and how to find them in graphs.

Alternatively, perhaps students choose not to report more complex relationships like interactions either because they do not fully understand them or because they are unsure of their ability to correctly articulate them.

Results from Experiment 4 demonstrated that although students who receive no specialized training are capable of interpreting relatively difficult graphs with above chance accuracy, their accuracy could still be much improved. Consistent with findings in the graph design literature, results from Experiments 4 and 5 indicate that students are faster to verify true-false statements in an immediate fact-retrieval task when graphs contain labels than when they contain legends. Moreover, a comparison of Experiments 4 and 5 suggests that individuals who received no specialized instruction were more accurate in responding to graphs with labels than graphs with legends, but this accuracy difference is diminished with the use of the graph comprehension tutorial. Thus, the graph tutorial is a potentially effective tool for teaching students how to deal with difficulties in graph comprehension. Furthermore, the tutorial may serve to negate possible advantages of labels over legends by better familiarizing students with varying graph formats and providing them with opportunities to practice interpreting such graphs.

The Notion of Desirable Difficulties in Graph Comprehension

Perhaps surprisingly, collective findings from Experiments 2-5 indicate that, in general, differences in graph format, at least for labels versus legends, do not critically affect task performance for complex multivariate data, whether the proportion of main effects and interactions described for a graph or the accuracy in responding to true-false questions about main effects of a graph in either immediate or long-term memory. The only exception was Experiment 4, wherein the graph tutorial was not completed prior to completion of the graph comprehension task and both RT and accuracy results reflected an advantage from labels. However, this task was an immediate fact retrieval task in which labels are typically favored, and therefore results were consistent with expectations. Thus, the idea of introducing legends into a graph as a potentially beneficial added visual difficulty did not bear out in these studies. However, it is also important to note that any potential differences in accuracy due to varying graph format may have been unobserved in Experiments 2 and 3 because of the inclusion of the tutorial, which possibly negated potential advantages of graph format by better familiarizing students with these formats and providing them with opportunities to practice interpreting such graphs.

In Experiment 3, no effect of graph format on accuracy was found in either the immediate or LTM tasks. Yet, when individual differences such as WM capacity are taken into consideration, there exists a trend in the data such that “desirable” difficulties may not be beneficial for all individuals. Although perhaps not immediately apparent, individuals need to have the WM capacity to deal with such difficulties, or else added difficulty may actually be detrimental to task performance in the long-term. Results from Experiment 3 suggest the potential that legends may actually harm some viewers (i.e., those with low WM span) some of the time (i.e., in the long-term). Additionally, increased open-mindedness was associated more specifically with increased accuracy on graphs containing legends in the immediate task. Thus, the potential benefits of desirable difficulties (e.g., legends) may be highly dependent both on an individual’s ability to deal with these demands and on an individual’s dispositions towards dealing with such demands.

However, there were some limitations in the current research that should be considered. First, “desirable difficulties” may only be desirable for certain kinds of tasks. Immediate or short-term memory tasks, especially fact-retrieval tasks, were not expected to show differences between graphs with added visual difficulties and those without. After all, conditions that affect learning, like the testing effect, have bigger impact at delay than with immediate testing. In fact, desirable difficulties such as retrieval practice only demonstrate a benefit for performance with delayed testing, whereas at immediate test performance is actually better for those conditions without added difficulty (e.g., Roediger & Karpicke, 2006). One potential reason why no differences between graph formats was observed in the LTM task of Experiment 3 may be because the delay period of 20 minutes between encoding and test was not long enough for the impact of added visual difficulty to be noticeable. For instance, in the prior example (Roediger & Karpicke, 2006), a longer delay period of one week elicited the beneficial testing effect.

Additionally, a task may lend itself better to a particular graph format depending on its goals or demands. It is possible that the goals or demands inherent in an immediate true-false verification task differ from the goals or demands inherent in an immediate or even delayed memory task. Fact-retrieval tasks in which viewers are looking for a particular piece of information or one specific relationship in the graph likely do not lend themselves to the same level of processing and comprehension of the full data set that would be expected to occur for a more open-ended task in which there is no single target variable or relationship to identify. This could be an additional reason why no effect of added difficulty was found in the LTM task of Experiment 3. Although viewers encoded the graph prior to receiving a question about the graph, all questions were specific to main effects in both immediate and LTM tasks and, consequently, viewers may not have processed all possible relationships in the graph within the fixed study time. Furthermore, retrieval based memory tasks such as those in the current study may be inherently different than recognition-based memory tasks. For example, pilot data from our lab showed that legends are more beneficial than labels for performance on a recognition-based memory task in which participants decided whether the presented graphs were the same or different than the ones they had viewed earlier. However, this is a very different task compared to the ones used in the current research, and is arguably much easier. Thus, desirable difficulties in graphs may be more beneficial in less difficult tasks, wherein there are fewer pre-existing challenges in the graph beyond that of the added difficulty, or in LTM tasks with much longer delays than in the current research.

Another possible limitation in the current research is that label and legend graphs may not have been different enough to elicit differential effects. Visual cues such as dotted versus solid lines and circle versus square end-points were present in both label and legend versions of the graphs, which may have led to double-encoding of variable information from both the visual cues and labels or legends. This may have limited the need to rely on either labels or legends, as it provided additional organizational or chunking information. Thus, graphs with legends may not have been sufficiently more challenging than graphs with labels in the current research. Additionally, the legend is organized differently than the labeled lines in a graph, which could lead to differences in the mapping process of individual lines to their referents. Future research could therefore include non-redundant visual cues or manipulate the order in which variables are listed in the legend compared to the order of labels on the graph.

Individual Differences as Key Players in Graph Comprehension

A much more crucial factor that has emerged from these studies is that of individual differences. General knowledge about graphs and WM span are clearly influential for task performance, as predicted by prior research relating to graph literacy and WM capacity. For example, in Experiment 2 graph literacy and WM span were highly predictive of the proportion of correct main effects and interactions students reported in the open-ended graph description task. In Experiment 3, individuals more highly skilled with graphs were more accurate in both immediate and LTM tasks, especially for graphs containing legends. This is consistent with the prediction that those more familiar with graphs would better know how to approach complex graphs or more easily learn from the included graph comprehension instructions. In contrast, WM span was more relevant for accuracy in the LTM task, especially for graphs containing legends. Two potential explanations for this finding were postulated: (1) Higher span individuals are perhaps better able to mentally transform the graphically presented data once it has been retrieved from LTM, in order to re-identify important relationships in the graph; or (2) Higher WM span individuals may be better able to encode the relationships between variables in the first place, because they perhaps are better able to keep track of the many variables while first interpreting the graph in the immediate task than low WM span individuals. Finally, Experiments 4 and 5 demonstrated that familiarity with graphs is important for graph comprehension, and WM capacity can impact the effectiveness of graph comprehension instruction since low WM span individuals benefited less from the graph tutorial than those with high WM span.

It has also been consistently shown across all five experiments that attitude or disposition can have a very large impact on graph comprehension across varying tasks and within both immediate and long-term memory. For example, Experiment 1 demonstrates that although format of the textbook reading may not influence immediate comprehension for that reading, attitude towards effortful thinking certainly is influential for comprehension of complex data in textbooks, such that individuals who enjoy more difficult thinking were more accurate in their immediate recognition responses. In Experiment 2, dispositional characteristics such as open-mindedness and NFC were both highly predictive of the proportion of correct main effects and interactions students reported in the open-ended graph description task. Experiment 3 demonstrated that open-mindedness, NFC, and cognitive reflection can affect graph comprehension. Open-mindedness was influential for overall accuracy in both the immediate and LTM tasks. Individuals with lower NFC performed better in the immediate task than those with high NFC, perhaps because less cognitive effort was involved in remembering within the short-term, whereas high NFC individuals may have found the immediate true-false verification task less challenging or engaging. Meanwhile, higher cognitive reflection scores were associated with better overall accuracy in LTM, suggesting that perhaps individuals who take the time or put in the required effort to reach a more deliberate, correct answer better remember this information later. Moreover, as seen in Experiments 4 and 5, attitude towards difficult thinking is a critical predictor of whether graph comprehension skills can be improved with instruction (i.e., some individuals may be more amenable to instruction or training than others). Specifically, students who do not enjoy effortful thinking are less likely to benefit from instruction, which suggests a need for educators to foster enjoyment of cognitive work in order for training of graphical skills to be effective.

Given that WM span has been consistently demonstrated as a limiting factor for graph comprehension task performance, as well as for instruction of graph comprehension skills, one important consideration for future research would be to further explore interactions between WM span level and desirable difficulties. Perhaps low WM capacity individuals could be trained to increase their WM span to help them avoid detrimental effects of added visual difficulties. Future research should also further examine interactions between WM span level and dispositions such as open-mindedness and NFC. Educators should consider ways in which to develop and encourage dispositions that are favorable for the improvement of much needed graph comprehension skills and, more generally, attitudes that are advantageous for work requiring cognitive effort. Such encouragement could be especially important for students who are already disadvantaged by low graphical literacy or low WM capacity, as positive dispositions may help close the gap between low and high skill students by providing low skill students with a helpful approach towards dealing with challenge. However, these suggestions raise the question of whether thinking dispositions such as AOT, NFC, and cognitive reflection can be taught or improved. Although several studies have shown improved thinking skills and processes potentially related to AOT with training intended to reduce susceptibility to bias (Baron, Badgio, & Gaskins, 1986) or increase evaluation of all relevant arguments (Perkins, Bushey, and Faraday, 1986), it remains unclear whether these interventions have long-lasting positive effects. Additional research on the teaching or training of thinking dispositions would provide valuable insight for educators hoping to encourage advantageous attitudes towards difficult thinking.

The current research focused on individual differences relating to graph skills and WM capacity, as well as dispositional factors like open-mindedness and NFC. However, future research could examine other individual differences that might play an influential role in graph comprehension, such as math or graph anxiety, more generalized test anxiety, and even susceptibility to stereotype threat. These particular factors would be predicted to detrimentally affect performance on graph comprehension tasks, and further understanding the nature of such disadvantages could help lead to successful interventions for coping with or alleviating them.

Building an Effective Tool for Instruction

Although the current research has demonstrated increased accuracy in questions relating to main effects with the use of a computerized graph tutorial, additional research is necessary to further develop this tutorial and to determine what aspects of the tutorial are most effective and what aspects should be changed or improved. A more theoretically grounded tutorial based on errors and a process model of graph interpretation would be an ideal to strive for with future research. One possibility would be to include both bar graphs and line graphs in the tutorial, with the idea that exposure to the same concepts in multiple graph formats would perhaps result in improved comprehension of main effects and interactions. Another possibility is to include demonstrations with only line graphs in the tutorial, for which transfer of the same concepts to a bar graph could then be checked (or vice versa). The ideal instructional end product would thus be tested on both comprehension and transfer.

A separate line of questioning could further investigate the concept of “static builds” used in the tutorial. Progressive animated builds are when graphs are progressively built up over time using some sort of animation, such as in power point or some other presentation software. Static builds are similar to these, except that, rather than using animation, graphs are gradually built by laying them out as separate frames on a page. These are more likely encountered in paper resources such as textbooks and handouts wherein it is not possible to include animations, and inclusions of static builds is a relatively frequent occurrence in some psychology textbooks. This is also similar to the concept of storytelling in the information visualization literature, whereby a story is laid out in a series of steps and each step contains visualizations based on data (Kosara & Mackinlay, 2013). In the graph tutorial of the current research, static builds are used to explain how to determine whether there are main effects present in 2x2x2 line graphs, although the effectiveness of static builds such as these have not yet been established. Thus, future research should examine whether sequential processing based static builds specifically are an effective method of improving graph comprehension, as this would also help to further develop a useful and effective graph tutorial for experimental and classroom applications.

Another possibility would be to consider switching from static builds to complete animations. Computer animations have been demonstrated as helpful for developing visualization skills, the ability to think about concepts or processes on a microscopic scale, and to build mental representations or models of concepts in a variety of fields, including chemistry (e.g., Dalton, 2003, as cited in Tasker & Dalton, 2006; Sanger, Phelps, & Fienhold, 2000; Williamson & Abraham, 1995), physics (e.g., Adams et al., 2008, parts I and II; Finkelstein et al., 2005; Kohnle, Douglass, Edwards, Gillies, Hooley, & Sinclair, 2010), and biology (e.g., Rotbain, Marbach-Ad, & Stavy, 2008). The benefit of computer animations has also been demonstrated in a wide range of age groups, from middle school (e.g., Kombartzky, Ploetzner, Schlag, & Metz, 2010) to high school (e.g., Rotbain et al., 2008) to college students (e.g., Kohnle et al., 2010; Williamson & Abraham, 1995). Some studies have even demonstrated that animations are more beneficial than static diagrams or visualizations presented on the board or in transparencies in class (e.g., Sanger et al., 2000) or better than a series of static pictures taken from the same animation (Kombartzky & Ploetzner, 2007). Animation could be useful in the context of simpler graphs, as it would allow for continuity of labels such that viewers would not need to re-identify them (Becker, Cleveland, & Wilks, 1988; Huber, 1987; Mackinlay, Robertson, & Card, 1991; Stuetzle, 1987).

It is important to note, however, that there are also some studies that demonstrate no benefit or even worse learning outcomes with the use of animations as compared to other types of external representations (e.g., Betrancourt, Morrison, & Tversky, 2002; Betrancourt & Tversky, 2000; Boucheix & Schneider, 2009; Mayer et al., 2005), though this may be due to differences in students' abilities to deal with the spatial and temporal demands inherent in many animations (Carpenter & Just, 1992; Lowe, 2003; Ploetzner, Bodemer, & Neudert, 2008). Therefore, it is unclear whether the benefits of animations would expand to include concepts relating to graph comprehension, or if static builds as defined in the current research would provide such a benefit in this context. It would be interesting to examine other types of static builds (e.g., bar graphs) and perhaps even move on to progressive animations to determine if progressive animations provide any benefit beyond that of static builds.

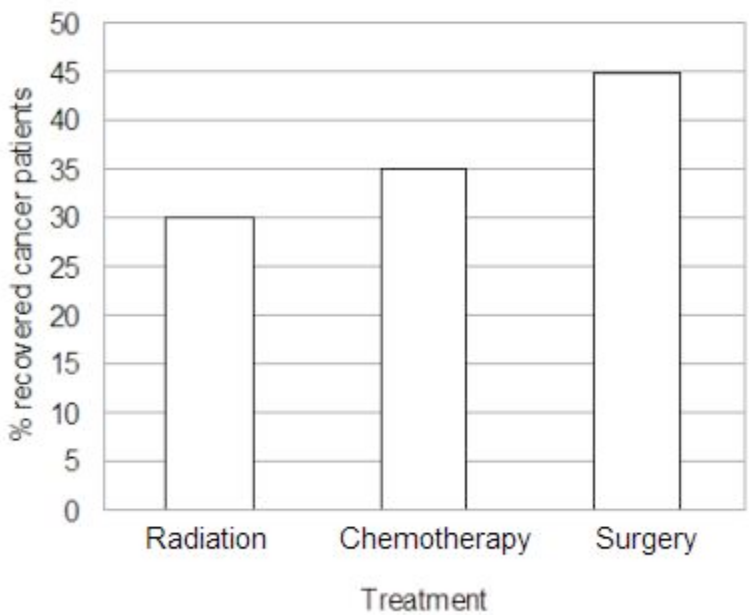
Finally, with the goal of further developing the current graph tutorial for application in experimental research and classroom education, additional research is needed to examine what types of graphs (e.g., line graphs, bar graphs, or both) are best for teaching main effects and interaction concepts. Line graphs seem to be best for emphasizing *x-y* trends (Carswell, Emery, & Lonon, 1993; Carswell & Wickens, 1987; Shah et al., 1999; Zacks & Tversky, 1999), so much so that viewers sometimes fail to completely interpret the remaining data in a complex graph or to recognize the same data plotted differently (Shah & Carpenter, 1995). Including only line graphs in a tutorial for graph comprehension may therefore be problematic for transfer of skills to other graph types. In contrast, bar graphs better emphasize discrete comparisons (Carswell & Wickens, 1987; Shah et al., 1999; Zacks & Tversky 1999) and are less biasing than line graphs with regards to what relationships in the data viewers will describe (Shah & Shellhammer, 1999).

Furthermore, future research should examine within-subject improvement with the use of a graph comprehension tutorial, as the current research compared student performance between groups. Improvement demonstrated in a pre- to post-tutorial graph comprehension measure would better demonstrate the tutorial as an effective instructional tool. Another interesting consideration would be whether the use of an effective tutorial can help alleviate the potentially detrimental effect of dispositional factors like math and graph anxiety or stereotype threat on performance on graph comprehension tasks. If so, such a tutorial would be a wonderful behavioral intervention that could potentially assist students in improving their academic performance for those subjects that rely heavily on graphical representations of data.

Appendix A

Graph Literacy Scale

Here is some information about cancer therapies.



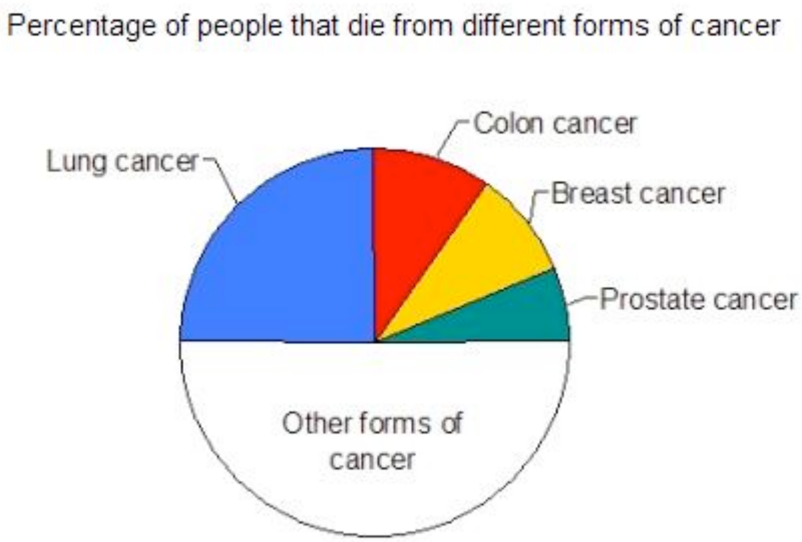
Q1. What percentage of patients recovered after chemotherapy?

%

Q2. What is the difference between the percentage of patients who recovered after a surgery and the percentage of patients who recovered after radiation therapy?

%

Here is some information about different forms of cancer.



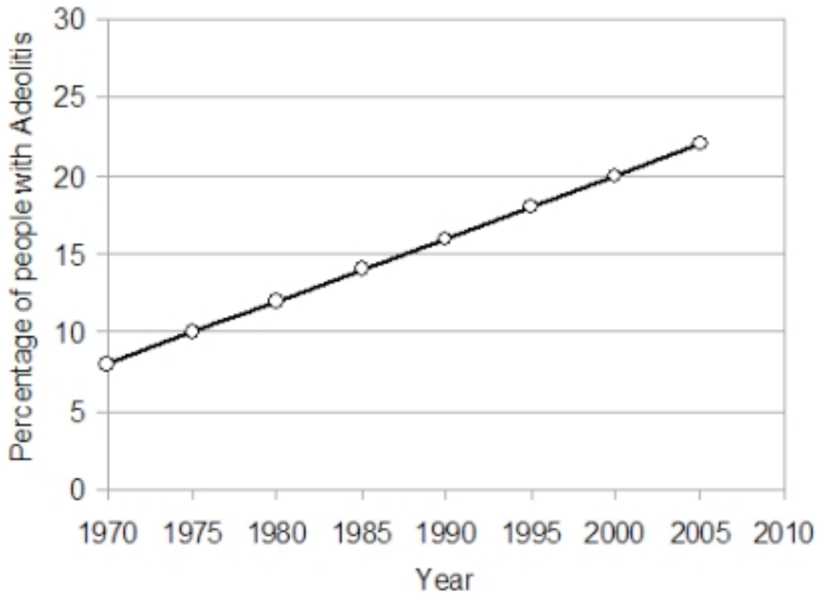
Q3. Of all the people who die from cancer, approximately what percentage dies from lung cancer?

[ ] %

Q4. Approximately what percentage of people who die from cancer die from colon cancer, breast cancer, and prostate cancer taken together?

[ ] %

Here is some information about an imaginary disease called Adeolitis.
Percentage of people with Adeolitis



Q5. Approximately what percentage of people had Adeolitis in the year 2000?

[ ] %

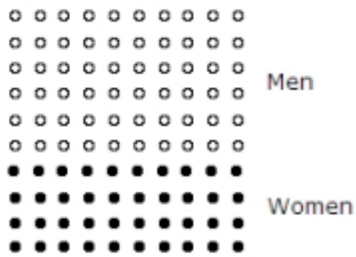
Q6. When was the increase in the percentage of people with Adeolitis higher?

From 1975 to 1980……………………………………………..1
From 2000 to 2005……………………………………………..2
Increase was the same in both intervals……......................3
Don't know……………………………………………………..4

Q7. According to your best guess, what will the percentage of people with Adeolitis be in the year 2010?

[ ] %

The following figure shows the number of men and women among patients with disease X. The total number of circles is 100.

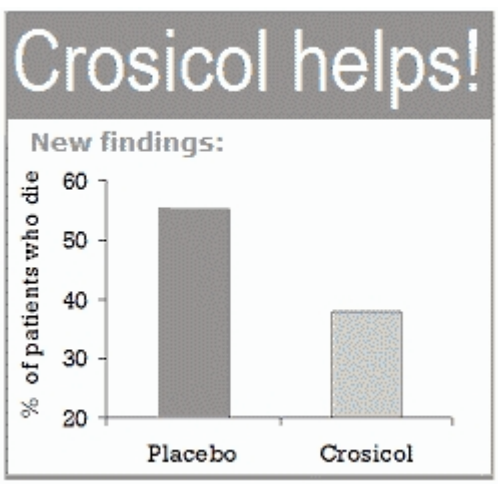


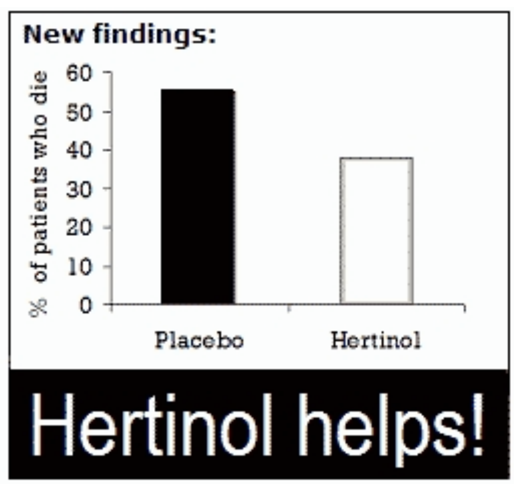
Q8. Of 100 patients with disease X, how many are women?

Q9. How many more men than women are there among 100 patients with disease X?

men

Q10. In a magazine you see two advertisements, one on page 5 and another on page 12. Each is for a different drug for treating heart disease, and each includes a graph showing the effectiveness of the drug compared to a placebo (sugar pill).

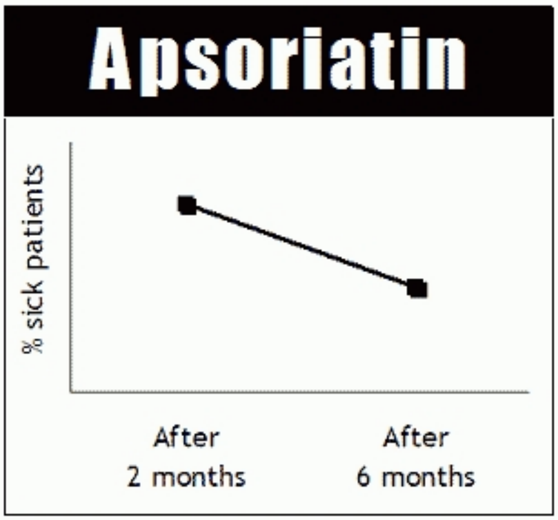


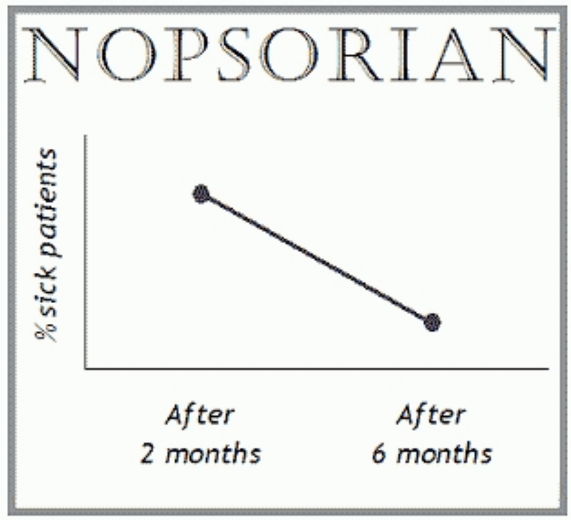


Compared to the placebo, which treatment leads to a larger decrease in the percentage of patients who die?

Crosicol………………………..1
Hertinol………………………..2
They are equal…………………3
Can't say………………………4

Q11. In the newspaper you see two advertisements, one on page 15 and another on page 17. Each is for a different treatment of psoriasis, and each includes a graph showing the effectiveness of the treatment over time.

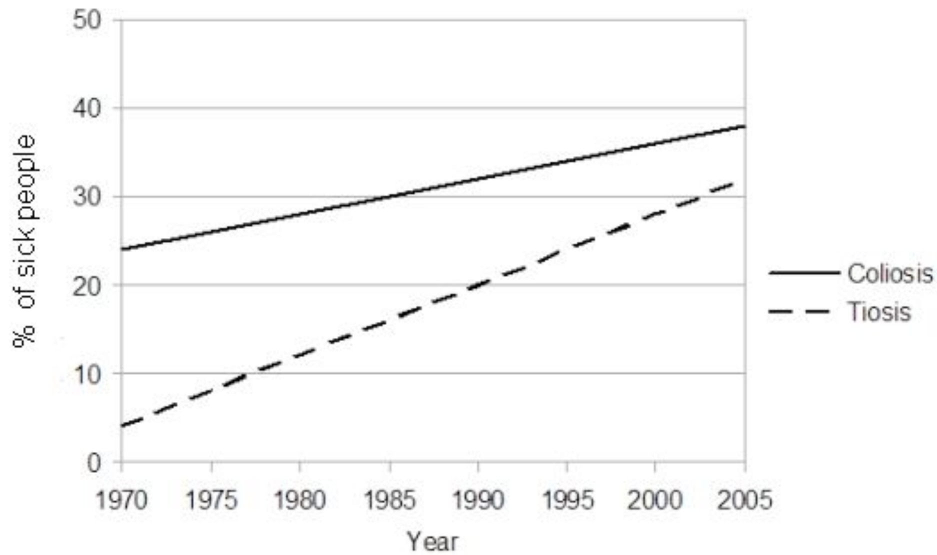




Which of the treatments contributes to a larger decrease in the percentage of sick patients?

Apsoriatin…………………1
Nopsorian…………………2
They are equal……………..3
Can't say…………………...4

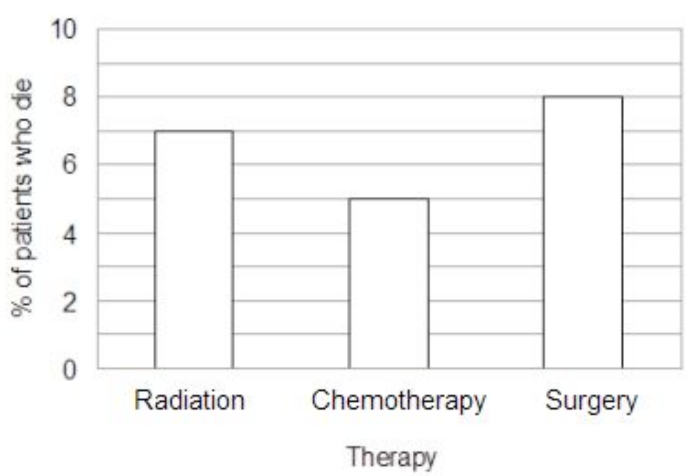
Q12. Here is some information about the imaginary diseases Coliosis and Tiosis.



Between 1980 and 1990, which disease had a higher increase in the percentage of people affected?

Coliosis……………………………1
Tiosis……………………………...2
The increase was equal……………3
Can't say…………………………..4

Q13. Here is some information about cancer therapies.



What is the percentage of cancer patients who die after chemotherapy?

[ ] %

Appendix B

Actively Open-Minded Thinking Scale

For each of the statements below, mark the alternative that best describes your opinion. There are no right or wrong answers so do not spend too much time deciding on an answer. The first thing that comes to mind is probably the best response.

1. A person should always consider new possibilities.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

2. A group which tolerates too much difference of opinion among its members cannot exist for long.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

3. Abandoning a previous belief is a sign of strong character.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

4. Basically, I know everything I need to know about the important things in life.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

5. Beliefs should always be revised in response to new information or evidence.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

6. Certain beliefs are just too important to abandon no matter how good a case can be made against them.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

7. Changing your mind is a sign of weakness.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

8. Coming to decisions quickly is a sign of wisdom.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

9. Considering too many different opinions often leads to bad decisions.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

10. Difficulties can usually be overcome by thinking about the problem, rather than through waiting for good fortune.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

11. Even though freedom of speech for all groups is a worthwhile goal, it is unfortunately necessary to restrict the freedom of certain political groups.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

12. Even if my environment (family, neighborhood, schools) had been different, I probably would have the same religious views.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

13. I believe we should look to our religious authorities for decisions on moral issues.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

14. I tend to classify people as either for me or against me.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

15. I believe letting students hear controversial speakers can only confuse and mislead them.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

16. I believe that loyalty to one's ideals and principles is more important than "open-mindedness."

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

17. I believe that laws and social policies should change to reflect the needs of a changing world.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

18. I believe that the "new morality" of permissiveness is no morality at all.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

19. I believe that the different ideas of right and wrong that people in other societies have may be valid for them.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

20. I consider myself broad-minded and tolerant of other people's lifestyles.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

21. I think that if people don't know what they believe in by the time they're 25, there's something wrong with them.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

22. I think there are many wrong ways, but only one right way, to almost anything.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

23. If I think longer about a problem I will be more likely to solve it.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

24. Intuition is the best guide in making decisions.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

25. It is a noble thing when someone holds the same beliefs as their parents.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

26. It is important to persevere in your beliefs even when evidence is brought to bear against them.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

27. It makes me happy and proud when someone famous holds the same beliefs that I do.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

28. Most people just don't know what's good for them.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

29. My beliefs would not have been very different if I had been raised by a different set of parents.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

30. My blood boils over whenever a person stubbornly refuses to admit he's wrong.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

31. No one can talk me out of something I know is right.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

32. Of all the different philosophies which exist in the world there is probably only one which is correct.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

33. Often, when people criticize me, they don't have their facts straight.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

34. One should disregard evidence that conflicts with your established beliefs.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

35. People should always take into consideration evidence that goes against their beliefs.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

36. Someone who attacks my beliefs is not insulting me personally.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

37. There are basically two kinds of people in this world, good and bad.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

38. There are two kinds of people in this world: those who are for the truth and those who are against the truth.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

39. There are a number of people I have come to hate because of the things they stand for.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

40. There is nothing wrong with being undecided about many issues.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

41. What beliefs you hold have more to do with your own personal character than the experiences that may have given.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

Appendix C

Need for Cognition Scale

For each of the statements below, please indicate to what extent the statement is characteristic of you. If the statement is extremely uncharacteristic of you (not at all like you) please mark a "1"; if the statement is extremely characteristic of you (very much like you) please mark a "5". There are no right or wrong answers so do not spend too much time deciding on an answer. The first thing that comes to mind is probably the best response. There is no time limit, but work as quickly as possible.

1. I would prefer complex to simple problems.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

2. I like to have the responsibility of handling a situation that requires a lot of thinking.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

3. Thinking is not my idea of fun.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

4. I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

5. I try to anticipate and avoid situations where there is likely a chance I will have to think in depth about something.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

6. I find satisfaction in deliberating hard and for long hours.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

7. I only think as hard as I have to.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

8. I prefer to think about small, daily projects to long-term ones.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

9. I like tasks that require little thought once I've learned them.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

10. The idea of relying on thought to make my way to the top appeals to me.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

11. I really enjoy a task that involves coming up with new solutions to problems.

1 2 3 4 5

Does Not Describe Me At All | Describes Me Perfectly

12. Learning new ways to think doesn't excite me very much.

1 2 3 4 5

Does Not Describe Me At All | Describes Me Perfectly

13. I prefer my life to be filled with puzzles that I must solve.

1 2 3 4 5

Does Not Describe Me At All | Describes Me Perfectly

14. The notion of thinking abstractly is appealing to me.

1 2 3 4 5

Does Not Describe Me At All | Describes Me Perfectly

15. I would prefer a task that is intellectual, difficult and important to one that is somewhat important but does not require much thought.

1 2 3 4 5

Does Not Describe Me At All | Describes Me Perfectly

16. I feel relief rather than satisfaction after completing a task that required a lot of mental effort.

1 2 3 4 5

Does Not Describe Me At All | Describes Me Perfectly

17. It's enough for me that something gets the job done; I don't care how or why it works.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

18. I usually end up deliberating about issues even when they do not affect me personally.

1	2	3	4	5
Does Not Describe Me At All				Describes Me Perfectly

Appendix D

Cognitive Reflection Test

Below are three items that vary in difficulty. Answer as many as you can.

(1) A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _____ minutes

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days

Appendix E

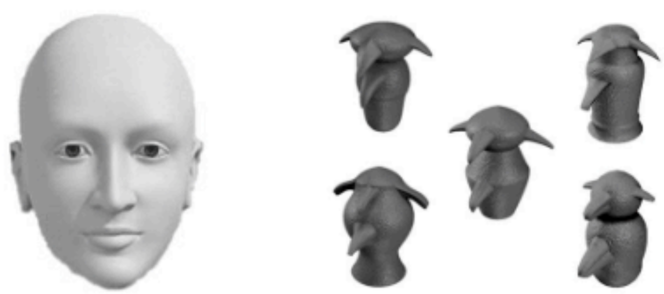
Experiment 1 Modified Textbook Excerpt (Goldstein, 2008)

Introductory page for all conditions:

Although we can associate specific parts of the brain with specific functions, this does not mean that the functioning of different parts of the brain is rigid and fixed. One of the brain's properties that enables it to adapt to the environment is its ability to change, so that it responds best to what is commonly encountered in the environment. Thus, although it may be important for parts of the brain to be specialized to carry out specific functions, the brain must also be able to adapt to the specific environment within which a person or animal lives.

There is a great deal of evidence that the nervous system achieves this adaptation to the environment through a mechanism called experience-dependent plasticity, which causes neurons to develop so they respond best to the types of stimulation to which a person or animal has been exposed. Experience-dependent plasticity has been demonstrated in humans using the brain imaging technique of fMRI. The starting point for this research is the finding that there is an area in the temporal lobe of the brain called the fusiform face area (FFA) that contains many neurons that respond best to faces.

Isabel Gauthier and coworkers (1999) determined whether this response to faces might be due to experience-dependent plasticity by measuring the level of activity in the FFA in response to faces (like the one on the bottom left below) and to objects called Greebles (pictured on the right below). Greebles are families of computer-generated "beings" that all have the same basic configuration but differ in the shapes of their parts (just like faces).



Text Only Condition:

Gauthier and her colleagues observed the fusiform face area (FFA) response, or the brain activity in the fusiform face area as measured by fMRI as participants view Greebles or faces. They found that faces activate neurons in the FFA, but Greebles do not activate the FFA. Thus, neurons in the FFA showed a greater response to faces than to Greebles. In other words, before training, the faces cause a large response in the FFA, and the Greebles cause a very small response.

Gauthier then gave her participants extensive training in "Greeble recognition" over a 4-day period. These training sessions, which required that each configuration of Greeble be labeled with a specific name, turned the participants into "Greeble experts". After training, the FFA is activated both by faces and by Greebles, such that the FFA responded almost as well to Greebles as to faces. Apparently, the FFA contains neurons that respond not just to faces, but to other complex objects as well. The particular objects to which the neurons respond best are established by experience with the objects.

In fact, in other studies, Gauthier has also shown that neurons in the FFA of people who are experts in recognizing cars and birds respond well not only to human faces, but to cars (for the car experts) and to birds (for the bird experts; Gauthier et al., 2000). Thus, the property of experience-dependent plasticity means that although the brain is organized so that specific areas process specific kinds of information, its functioning can also be "tuned" to operate best within a specific environment.

Text with Irrelevant Picture Condition:

Gauthier and her colleagues observed the fusiform face area (FFA) response, or the brain activity in the fusiform face area as measured by fMRI as participants view Greebles or faces. They found that faces activate neurons in the FFA, but Greebles do not activate the FFA. Thus, neurons in the FFA showed a greater response to faces than to Greebles. In other words, before training, the faces cause a large response in the FFA, and the Greebles cause a very small response.

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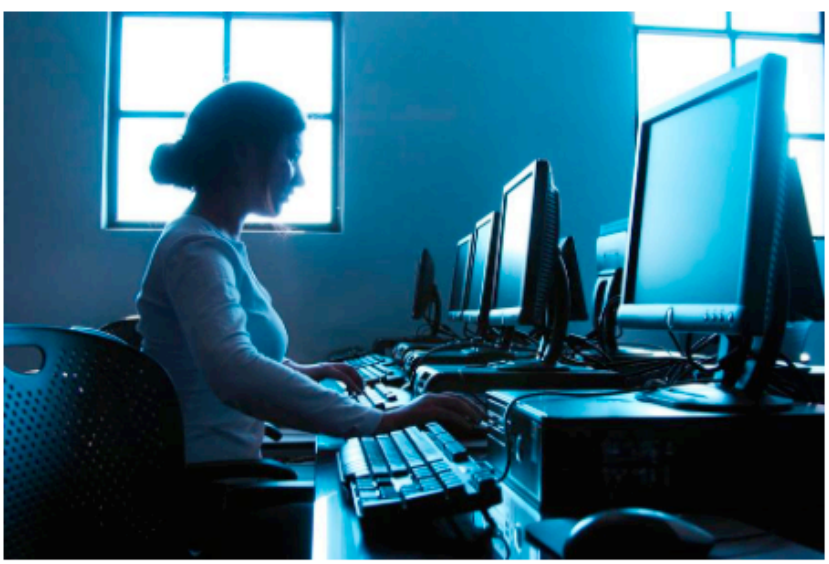
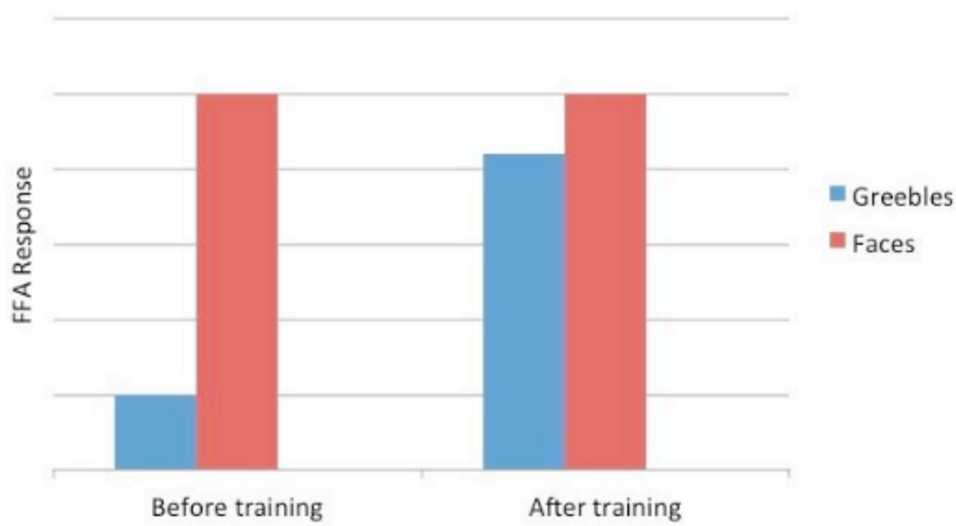


Text with Relevant Graph Condition:

Gauthier and her colleagues observed the fusiform face area (FFA) response, or the brain activity in the fusiform face area as measured by fMRI as participants view Greebles (blue bars) or faces (red bars). They found that faces activate neurons in the FFA, but Greebles do not activate the FFA. Thus, neurons in the FFA showed a greater response to faces than to Greebles (as indicated by the left pair of bars in the graph). In other words, the left pair of bars indicate that before training, the faces cause a large response in the FFA, and the Greebles cause a very small response.

Gauthier then gave her participants extensive training in "Greeble recognition" over a 4-day period. These training sessions, which required that each configuration of Greeble be labeled with a specific name, turned the participants into "Greeble experts". After training, the FFA is activated both by faces and by Greebles, such that the FFA responded almost as well to Greebles as to faces (as indicated by the right pair of bars in the graph). Apparently, the FFA contains neurons that respond not just to faces, but to other complex objects as well. The particular objects to which the neurons respond best are established by experience with the objects.

In fact, in other studies, Gauthier has also shown that neurons in the FFA of people who are experts in recognizing cars and birds respond well not only to human faces, but to cars (for the car experts) and to birds (for the bird experts; Gauthier et al., 2000). Thus, the property of experience-dependent plasticity means that although the brain is organized so that specific areas process specific kinds of information, its functioning can also be "tuned" to operate best within a specific environment.



Appendix F

Experiment 1 Free Response Question Coding Scheme

0 = No response

1 = Response completely unrelated to textbook excerpt or Greeble study data or findings

2 = More general conclusion of textbook excerpt (not specific to actual Greeble study data or findings)

3 = Correct description of Greeble study data or findings (e.g., overall, FFA response to faces was more than FFA response to Greebles; FFA response to faces was constant, while FFA response to Greebles increased from pre- to post-training)

4 = Incorrect description of Greeble study data or findings

5 = Describes study method, but not actual data or findings or more general conclusions based on findings

Appendix G

Demographic Questionnaire

Participant information is collected primarily for the purpose of reporting demographic data to funding institutions. Your name and email will not be reported.

1. Gender _____ F _____ M

2. Education (highest level attained or most recent year of school completed)
____

3. Current Major _______________________ Minor _______________

4. Birthdate ____/_____/_______ 5. Age _______________

6. Are you right or left handed?
__ Right
__ Left

7. Ethnicity (Please select only one)
___ Hispanic
___Not Hispanic

8. Race (Please select only one)
__ American Indian/Alaska Native
__ Asian
__ Native Hawaiian or Other Pacific Islander
__ Black or African American
__ White/Caucasian
__ More than one
__ Other/Unknown

9. Do you consider yourself familiar with (mark all that apply):
__ Line Graphs
__ Wireframe (3d) graphs
__ Bar Graphs
__ Pie Charts
__ Contour plots

10. Do you use graphs frequently in your occupation/courses? _____________

11. Do you prefer graphs or tables if you need to look at some numerical data?________

12. How many statistics classes have you taken in college?____________
Please list titles
____
____
____

13. How many math classes have you taken in college?_____________
Please list titles
____
____
____

14. What was your Math Section SAT Score (out of 800)/ACT Math Score?__________

15. Do you think of yourself as a math person? Do you think of yourself as a scientific person? How confident are you with your scientific reasoning skills?

16. Are you comfortable with looking at numbers and statistics?

17. Do you feel comfortable with looking at graphs and understanding graphs?

Appendix H

Exit Survey

Thank you for your participation!!
As part of our research, we are interested in your input and impressions of the experiment you have just completed. Please answer the following questions to the best of your ability:

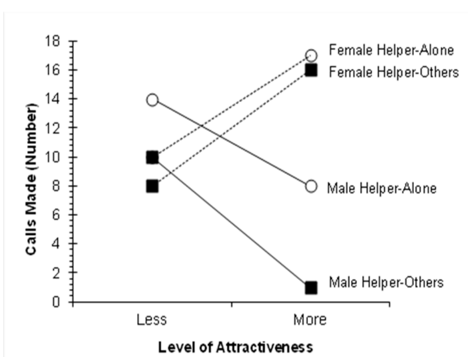
1. Did you employ any strategies or "tricks" to help you in the experiment?

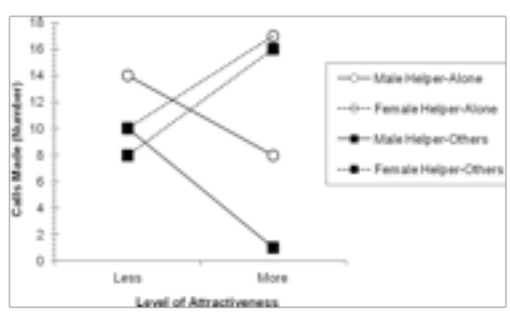
2. Did you think that certain graphs were more difficult than others? If so, what made them more or less difficult?

3. Did you have a preference for certain graphs over other graphs? If so, what did you prefer and why?

4. Which of the following type of graph did you prefer (circle one)?

Graphs with Labels OR Graphs with Legends





5. What do you think the point of the experiment was? What kind of thinking or memory was it testing?

Appendix I

Experiment 2 Sample Open-ended Graph Description Task Coding Scheme

Graph 1: ____________________

Correct

1. Description of Study (not data) Yes No
2. Main Effect of __________________________________ Yes No
3. Main Effect of __________________________________ Yes No
4. Main Effect of __________________________________ Yes No
5. 2-way Interaction of ______________________________________ Yes No
6. 2-way Interaction of ______________________________________ Yes No
7. 2-way Interaction of ______________________________________ Yes No
8. Partial 2-way Interaction Yes No How many?_________
9. Partial 3-way Interaction Yes No

Incorrect

1. Description of Study (not data) Yes No
2. Main Effect of __________________________________ Yes No
3. Main Effect of __________________________________ Yes No
4. Main Effect of __________________________________ Yes No
5. 2-way Interaction of _______________________________________ Yes No
6. 2-way Interaction of _______________________________________ Yes No
7. 2-way Interaction of _______________________________________ Yes No
8. Partial 2-way Interaction Yes No How many?_________
9. Partial 3-way Interaction Yes No

Appendix J

Sample True-False Statements for Experiments 3-5

1. On average, the mice that were in a simple learning environment took more time to reach the platform than those that were in a complex learning environment. (FALSE)

2. On average, the mice that did not receive a transplant took less time to reach the platform than the mice that did receive a transplant. (FALSE)

3. On average, students who had low levels of achievement performed better on the task than those students who had high levels of achievement. (TRUE)

4. On average, students who were motivated intrinsically scored lower than those students who were motivated extrinsically. (TRUE)

5. On average, people who do not drink alcohol rate both themselves and others as being riskier than those people who do drink alcohol. (FALSE)

6. On average, people rate themselves as being greater risk takers than their peers. (TRUE)

7. On average, children engaged in play activities rated their partner as more creative than those children who were engaged in academic activities. (FALSE)

8. On average, children who were correctly informed about their partner's level of art instruction rated their partner as having a higher creativity rating than those who were misinformed. (TRUE)

9. On average, women had fewer domestic violence arrests than men. (TRUE)

10. On average, people who did not receive counseling had more domestic violence arrests than people who did receive counseling. (FALSE)

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