

INFLUENCE OF VISUAL CUEING AND OUTCOME FEEDBACK ON PHYSICS
PROBLEM SOLVING AND VISUAL ATTENTION

by

AMY ROUINFAR

B.S., Florida State University, 2010

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

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Department of Physics
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

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Abstract

Research has demonstrated that attentional cues overlaid on diagrams and animations can help students attend to the relevant areas and facilitate problem solving. In this study we investigate the influence of visual cues and outcome feedback on students' problem solving, performance, reasoning, and visual attention as they solve conceptual physics problems containing a diagram. The participants (N=90) were enrolled in an algebra-based physics course and were individually interviewed. During each interview students solved four problem sets while their eye movements were recorded. The problem diagrams contained regions that were relevant to solving the problem correctly and separate regions related to common incorrect responses. Each problem set contained an initial problem, six isomorphic training problems, and a transfer problem. Those in the cued condition saw visual cues overlaid on the training problems. Those in the feedback conditions were told if their responses (answer and explanation) were correct or incorrect. Students' verbal responses were used to determine their accuracy. The study produced two major findings. First, short duration visual cues coupled with correctness feedback can improve problem solving performance on a variety of insight physics problems, including transfer problems not sharing the surface features of the training problems, but instead sharing the underlying solution path. Thus, visual cues can facilitate re-representing a problem and overcoming impasse, enabling a correct solution. Importantly, these cueing effects on problem solving did not involve the solvers' attention necessarily embodying the solution to the problem. Instead, the cueing effects were caused by solvers attending to and integrating relevant information in the problems into a solution path. Second, these short duration visual cues when administered repeatedly over multiple training problems resulted in participants becoming more efficient at extracting the relevant information on the transfer problem, showing that such cues can improve the automaticity with which solvers extract relevant information from a problem. Both of these results converge on the conclusion that lower-order visual processes driven by attentional cues can influence higher-order cognitive processes associated with problem solving.

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Dedication

For my grandmother, Theresa.

Chapter 1 - Introduction and Relevant Literature

Introduction

Vision is a vitally important mode of communication. Images of all kinds including diagrams, graphs, pictures, and many others are ubiquitous in educational materials. While many of these images facilitate learning, others might impede learning through added cognitive load. For instance, a graph showing too many different kinds of data can be difficult to interpret. In order to enable learners to use images effectively and design images that facilitate learning, it is imperative that we understand the factors that affect how visual information is used by learners.

There are many visual learning environments in physics (including problem diagrams) which contain information that is both relevant and irrelevant to the task at hand. By helping the learner to focus their attention (and therefore their cognitive resources) on the relevant information, learning can be facilitated. Problem solving is a major area of concern in physics education. Problem solving has deep cognitive underpinnings and has been studied extensively since the last century (for a review see Jonassen, 2011). Jonassen defines a problem as a “question or issue that is uncertain and so must be examined and solved.” From the standpoint of cognitive psychology, there are three major aspects to problem solving—it is purposeful, involves cognitive rather than automatic processes, and it only exists when the solver lacks the relevant knowledge to immediately produce a solution (Eysenck & Keane, 2005). Visual cueing is a method which can aid students in the redirection of their attention and can help them attend to and notice relevant information in the problem which they may have previously ignored. The learner may be more likely to retrieve relevant information from long-term memory once they have attended to the relevant features in the environment. Visual cueing has been studied in a variety of contexts and has been found to facilitate both comprehension and problem solving.

In this chapter I provide a brief overview of the previous literature on the relationship between eye movements and cognition. Previous research on visual attention in physics, the use of visual cues in educational environments, and the theoretical foundation of this work are also discussed. Finally, the motivations of this work, research questions, and organization of this dissertation are presented.

Relevant Literature

Selective Attention and Eye Movements

As educational researchers, we are interested in understanding the processes involved in learning and problem solving. To understand these we would like to measure such processes in real time without interfering with the processes themselves. Recording eye movements is a method which has been used widely in many disciplines to capture cognitive processes in real time (Charness et al., 2001; Hegarty et al., 2010; Epelboim & Suppes, 2001; Rayner, 1998). With this method, a series of saccades (i.e., when eyes are in motion) and fixations (i.e., when eyes are stationary at a specific spatial location) are recorded with an eye tracker. The locations, durations and order of the saccades and fixations are then analyzed to understand the participants learning or problem solving process. There is an underlying assumption in eye tracking research that there is a connection between eye movements and cognitive processing such that the direction of gaze and the mind are aligned in a one-to-one immediate fashion. This was articulated by Just and Carpenter as the “eye mind assumption” (1980) who studied eye movements during reading and explained that “the eye remains fixated on a word as long as the word is being processed. So the time it takes to process a newly fixated word is directly indicated by the gaze duration.”

We assume that eye movements are linked to attentional selection as proposed by the rubber band model of eye movements and attention (Henderson, 1992, 1993). Specifically, at the beginning of each eye fixation, attention is aligned with the point of fixation (Glaholt et al., 2012; Larson et al., 2014; van Diepen & d'Ydewalle, 2003), but by roughly 80 ms before the next eye movement, covert attention is shifted to the to-be-fixated object (Caspi et al., 2004; Deubel & Schneider, 1996; Kowler et al., 1995), after which the eyes make a saccade to the newly attended object. Thus, although attention may be at a different location than the point of fixation (especially in the last 80 ms of a fixation, called covert attention) (Caspi et al., 2004), if the eyes are sent to a location, we know that attention was there at the beginning of the fixation. One can therefore retrospectively measure the location of attentional selection by measuring eye fixation locations, called overt attention.

Research on attentional selection has made tremendous strides in explaining the effects of stimulus characteristics, or bottom-up influences, on overt attention. These studies have shown

that stimulus saliency, as measured by contrast along various feature dimensions coded by early visual cortex (e.g., luminance, color, orientation, and motion), plays a moderately strong causal role in determining where the eyes are sent (Irwin et al., 2000; Itti & Koch, 2000; Mital et al., 2010). Other research has shown non-stimulus-based effects, or top-down influences, on overt attention. These top-down influences can be further divided between those that are involuntary and automatic, based on experience and learning, called mandatory top-down processes, and those that are voluntary and effortful, called volitional top-down processes (Baluch & Itti, 2011). Numerous studies have shown evidence of mandatory top-down effects on overt attentional selection in scenes (e.g., attention to stop signs when they are in expected locations, such as intersections, but not in unexpected locations, such as the middle of a block) (Shinoda et al., 2001; Theeuwes & Godthelp, 1995). A separate body of research has shown effects of volitional top-down processes on overt attention in more laboratory-based tasks (e.g., the anti-saccade task, in which one looks in the opposite direction from a salient visual stimulus) (Everling & Fischer, 1998). Overall, mandatory top-down processes have been shown to generally have a stronger influence on overt attentional selection than bottom-up visual saliency (Einhauser et al., 2008; Foulsham & Underwood, 2007; Henderson et al., 2007). Conversely, because volitional top-down processes require executive attentional and working memory resources, they generally have weaker effects on overt attentional selection than bottom-up saliency, as shown by the antisaccade task, in which the sudden appearance of a simple stimulus is very difficult to avoid reflexively looking at, while it takes a conscious effort to looking in the opposite direction (Guitton et al., 1985; Mitchell et al., 2002). Nevertheless, a far fewer number of studies have investigated the relationships between bottom-up and top-down processes and overt attentional selection in higher-level cognitive tasks such as problem solving.

Overt Attentional Selection in Problem Solving

Prior research on eye movements and problem solving has shown that overt attention can illuminate the cognitive processes involved in problem solving (Bilalić et al., 2008; Eivazi & Bednarik, 2010, 2011; Epelboim & Suppes, 2001; Grant & Spivey, 2003; Jones, 2003; Knoblich et al., 2001; Knoblich et al., 2005; Lin & Lin, 2014; Madsen et al., 2012, 2013a, 2013b; Susac et al., 2014; Thomas & Lleras, 2007, 2009). However, we are particularly interested in two directions of causal relationships between overt attentional selection and the higher-level

cognitive processes involved in problem solving: 1) the causal relationship starting from higher-level cognitive processes involved in problem solving and ending with attentional selection; and 2) the reverse causal relationship starting from attentional selection and ending with the higher-level cognitive processes involved in problem solving. A relatively small number of studies have investigated each of these relationships, with some speaking more to the effect of higher-level cognitive processes in problem solving on attentional selection (Epelboim & Suppes, 2001; Knoblich et al., 2001; Madsen et al., 2012), and others speaking more to the effect of attentional selection on higher-level cognitive processes in problem solving (Cameron et al., 2002; Epelboim & Suppes, 2001; Grant & Spivey, 2003; Lin & Lin, 2014; Susac et al., 2014; Tai et al., 2006; Thomas & Lleras, 2007, 2009).

Research on the effect of the cognitive processes involved in problem solving on overt attentional selection has shown that mandatory top-down processes based on prior knowledge can enable solvers to rapidly attend to relevant information when solving a problem (Madsen et al., 2012; Epelboim & Suppes, 2001). In the most extreme cases, based on prior knowledge, an expert may attend to the relevant information in a problem within the time frame of a single eye fixation, while a novice may instead take much more time while attending to various sources of irrelevant information (Charness et al., 2001; Reingold et al., 2001). Just as importantly, however, even if the solver has previously activated irrelevant knowledge, leading to an impasse, restructuring the problem representation can lead to shifting overt attention away from irrelevant information to relevant but previously ignored information (Jones, 2003; Knoblich et al., 2001).

Research on the effect of attentional selection on the cognitive processes involved in problem solving suggests that there are at least two qualitatively different types of effects. First, attentional selection can lead either to processing relevant information, which facilitates problem solving by activating relevant domain knowledge, leading to finding a viable solution path, or processing irrelevant information, which impedes problem solving by activating irrelevant knowledge, leading to an incorrect solution path (Madsen et al., 2012, 2013a; Grant & Spivey, 2003; Thomas & Lleras, 2007, 2009). This effect of attentional selection on problem solving determines whether or not the solver, in a manner of speaking, gets through the starting gate to finding a viable solution path. Second, if a solver has gotten through the starting gate by attending to relevant information, further attentional selection of aspects of that relevant

information appears to be important for not only extracting further relevant information, but also refreshing their working memory (WM) representations used in finding the solution path. Here, we assume that problem solving occurs in WM (Epelboim & Suppes 2001; Ohlsson 1992), and that WM has a limited capacity (Baddeley, 1994; Cowan, 2001; Luck & Vogel, 1997). Thus, if the process of finding a viable solution path involves establishing relationships between numerous conceptual entities, solvers may experience difficulties caused by exceeding their WM capacity (Epelboim & Suppes 2001). Because maintaining representations in WM requires attention (Cowan, 2001), one can refresh WM representations by attending to them (Awh et al., 1998; D'Esposito et al., 1999; Hale et al., 1996), for example by repeatedly refixating the eyes on the to-be-processed items (Zelinsky et al., 2011). Thus, during problem solving, attentional selection, as evidenced by refixating relevant information, can facilitate finding a solution path by refreshing the WM representations for the fixated items (Epelboim & Suppes, 2001; Lin & Lin, 2014; Susac et al., 2014; Tai et al., 2006).

A different way in which overt attentional selection can facilitate problem-solving processes in WM is through sustained attention, which involves inhibiting overt and covert attentional shifts. Specifically, when a solver is engaged in complex problem solving processes in WM, longer than normal processing times are sometimes needed in order to attend to the current contents of working memory. In those cases, it would be counter-productive to move attention and the eyes to a new location, which automatically triggers extracting the new information there into WM (Belopolsky et al., 2008), potentially displacing some of the current WM contents (Zelinsky & Loschky, 2005). Instead, the solver may inhibit moving the eyes, resulting in a longer eye fixation at the current location (Findlay & Walker, 1999). Thus, during the process of breaking an impasse (i.e., the moment of insight), problem solvers will often produce longer fixation durations, rather than making more fixations on different items (Jones, 2003; Knoblich, et al., 2001; Velichkovsky et al., 2002).

Visual Cueing

Visual cueing is a method which can aid students in the redirection of their attention and can help them attend to and notice relevant information in the problem which they may have previously ignored. The learner may be more likely to retrieve relevant information from long-

term memory once they have attended to the relevant features in the environment. Visual cueing has been studied in a variety of contexts and has been found to facilitate both comprehension and problem solving.

Visual cues have been shown to improve comprehension in a variety of contexts. Kalyuga et al. (1999) found that color-coded cues used to help students relate elements of a diagram of “push button” circuit to the accompanying text had higher comprehension scores than those who were not provided with the color-coding. Tabbers et al. (2004) studied the use of visual cues in a lesson on instructional design which contained a set of slides with diagrams accompanied by text. They found that students who saw the colored cues which highlighted elements of the diagram when students clicked on the related text had higher retention scores. Similarly, Jamet et al. (2008) investigated how visual cues could increase comprehension when spoken explanation and labeled diagrams of the brain were presented to students. When an area of the brain was mentioned in the spoken explanation, it was colored red in the diagram. Those who saw the visual cues had higher scores on retention questions. Scheiter and Eitel (2010) investigated student learning with text and diagrams of the heart. The cue highlighted important words in the text and labeled in the diagram. Color-coding was also used. The researchers found that these cues improved students’ understanding of the relationship between text and diagram and increased visual attention to the diagram. Research done by de Koning et al. (2007) found that spotlight cues on a complex cardiovascular animation increased comprehension and transfer. The spotlight cues slightly darkened all parts of the animation except the section being cued. Boucheix and Lowe (2010) looked at how different visual cues affected attention and comprehension of an animated of a piano system and found that the spreading color cued condition had significantly higher comprehension scores. They also found that the areas most relevant for understanding the piano system’s functions were fixated on for longer times in the spreading color cue condition. Together, these studies suggest that visual cues can help students integrate and better comprehend information from text, spoken explanations, static diagrams, and animations.

Visual cueing has also been found to improve problem solving performance. Velichovksy (1995) found that novices who viewed expert solvers’ real-time eye movements had improved performance while solving a picture puzzle (picture cut up into pieces and pieces

scrambled). Grant and Spivey (2003) investigated the effectiveness of visual cues while solving an insight problem. The diagram was manipulated so that either the relevant or irrelevant area pulsed or the diagram remained static. Those who viewed the relevant area pulsing (expanding by six pixels repeatedly) spent more time attending to the relevant area and were significantly more likely to provide a correct solution than those who saw the irrelevant area pulsing or a static diagram. The researchers suggested that drawing attention to the relevant area of a diagram can induce correct solving of an insight problem and visual attention may influence cognitive processing. In a follow up study conducted by Thomas and Lleras (2007), visual cues were overlaid on the problem diagram for four seconds at the end of a 26 second free viewing period. This was repeated until the participant answered correctly or a maximum of twenty times. The visual cues moved in four different patterns, one of which embodied the solution to the problem. Those in the embodied solution group were significantly more likely to solve the problem correctly.

Our research was inspired by the groundbreaking work of Thomas and Lleras (2007, 2009), which demonstrated that shifting overt or covert attention in ways that embody the solution to Duncker's (1945) tumor problem improved performance on it, even without solvers being aware of the relevance of the cueing to finding the problem's solution. The concept of having attentional movement trajectories embody the solution to a problem, while powerful, may not apply to solving a wide array of problems. However, the simpler relationship between what is selected for visual attention and how that affects problem solving cognitive processes can be investigated in most if not all problems involving figures. Our particular approach to investigating this issue has been to use specific physics problems that contain two distinct regions, those associated with well-documented misconceptions and those associated with correctly solving the problems. In this way, a direct connection can potentially be found between overt attentional selection and problem solving cognitive processes. The results of these studies showed that when attempting to solve such problems, solvers' overt attention was strongly guided by mandatory top-down processes (prior knowledge, either correct or mistaken) to either the relevant or irrelevant regions respectively (Madsen et al., 2012; 2013a). Importantly, those who overtly attended more to the relevant information were more likely to correctly solve the problems, and those who overtly attended to regions associated with well-documented misconceptions more frequently gave incorrect answers in line with those

misconceptions. This raised the question of whether guiding solvers' overt attention to the relevant information would facilitate their correctly solving those or similar problems.

In one study, we modified the bottom-up visual saliency (as measured by a computational model) of the relevant versus irrelevant regions in physics problems (by increasing or decreasing the luminance contrast of the lines in the problem diagrams) (Madsen et al., 2013b). Interestingly, we found that solvers' mandatory top-down processes (prior knowledge) guided their overt attention, overwhelming any potential effects of stimulus saliency (Madsen et al., 2013b). Nevertheless, as before, those who attended more to relevant information were more likely to correctly solve the problems (Madsen et al., 2012).

In a follow up study we provided students with visual cues modeled after correct solvers' eye movements to direct their attention to the relevant areas of problem diagrams (Madsen et al., 2013). Participants in this study (N=63) were randomly assigned to either the cued or uncued conditions, which differed by whether the participants saw conceptual physics problems overlaid with dynamic visual cues modeled after correct solver's eye movements (Madsen et al., 2012). Students in the cued condition were shown an initial problem, and if they answered that incorrectly, they were shown a series of up to four similar problems each with selection and integration cues overlaid on the problem diagrams. Students in the uncued condition were also provided a series of problems, but without any visual cues. If participants in either condition answered a problem correctly, they were presented with a transfer problem. We found that significantly more participants in the cued condition answered the problems overlaid with visual cues correctly on one of the four problem sets used and a subsequent uncued problem (the transfer problem) on a different problem set. Thus, getting solvers through the starting gate, by guiding their overt attention to relevant information, was often insufficient to facilitate correct problem solving.

One limitation of this study was that the students were not instructed of the purpose of the cues. The one of four problem sets in which the cued participants significantly outperformed uncued participants on the cued similar problems had very simple cue. Madsen et al. suggested that the unsuccessful cues could have been too complicated for students to properly encode during the six second duration. Additionally, the cues themselves may have also been too

abstract for students, as they were modeled after expert-like eye movements which could have been too streamlined and condensed for students to easily encode. One recommendation for future work included redesigning the cues to be simpler so that that may be more easily interpreted.

In sum, our prior work has shown that higher-level cognitive processes involved in physics problem solving very strongly guide solvers' overt attentional selection. Furthermore, overt attentional selection of relevant (rather than irrelevant) information is associated with a higher probability of correctly solving such problems. However, we have also shown that simply guiding solvers' overt attention to relevant areas of physics problems is often insufficient to correctly solve those problems, or transfer problems similar to them.

The function and mechanism of visual cueing can be interpreted through the lens of three theoretical frameworks. The first is Ohlsson's (1992) Representational Change Theory (1992), which deals with the cognitive mechanisms involved in solving insight problems, namely those problems that require insight rather than mere algorithmic calculations. The second is de Koning et al.'s (2009) framework for attentional cueing in instructional animations, which in turn builds on the third, Mayer's (2001) Cognitive Theory of Multimedia Learning, which is relevant to the use of multimodal information in learning. We also discuss the role of outcome feedback in learning.

Representational Change Theory

Representational Change Theory provides a framework to understand the cognitive mechanisms involved in solving problems that require conceptual insight, rather than purely algorithmic computation. This framework lends itself to our work on problem solving, as the problems we study are conceptual in nature and because they require the solvers to recognize the appropriate concepts to apply.

According to Representational Change Theory, the representation of a problem in the solver's mind mediates the knowledge that he or she retrieves from long-term memory. This retrieval is based on the activation of the related concepts or pieces of knowledge stored in long-term memory. The problem solver reaches an impasse when the way the problem is represented

does not allow for the retrieval of the necessary operators or possible actions needed to reach the desired goal state. To break the impasse, the problem representation in the solver's mind must be modified. A new mental representation serves as a retrieval cue for relevant operators in long-term memory, thereby extending the information available to the problem solver.

An impasse can be broken by one of the following mechanisms: elaboration, re-encoding, and constraint relaxation. Elaboration occurs when sufficient information has been added to the problem to enrich and extend the existing representation. When the learner replaces an existing representation with a different, more productive representation re-encoding has occurred. In constraint relaxation, the learner removes unnecessary, often self-imposed, constraints. Successfully breaking an impasse leads the problem solver to create a new mental representation of the problem allowing them to retrieve the relevant concepts or pieces of knowledge (i.e. activate the appropriate resources (Hammer, 2001)) thereby extending the information available to them. Insight is achieved upon the breaking of the impasse in which the retrieved knowledge operators are sufficient to solve the problem.

Framework for Attention Cueing

Physics problem solving lends itself to the use of multiple representations to visualize problem scenarios, relationships between quantities, and expressing mathematical relationships. Mayer's Cognitive Theory of Multimedia Learning (2001) pertains to the use of multimodal information in learning. Many physics problems require students to coordinate information provided in multiple modalities (e.g. problems with text and diagrams). Mayer identifies three distinct processes involved in learning from multimodal information – selection, organization, and integration. Selection is the process of attending to specific pieces of information. Using the selected information in each modality to create a coherent internal representation is organization. Integration involves combining the internal representations from different modalities with activated prior knowledge. These processes are all influenced by the prior knowledge that a learner has. Based on the Cognitive Theory of Multimedia Learning, de Koning et al. (2009) proposed a Framework for Attention Cueing that suggests that appropriately designed visual cues can facilitate all three processes.

Selection cues can facilitate problem solvers to attend to the relevant information within a visual representation. For instance, spotlight cues produced by reducing the luminance of all but relevant parts (de Koning et. al. 2007; 2010) have been shown improve learning. Similarly, Grant and Spivey (2003) found that movement of a critical part of a diagram increased fixation times around that part and improved performance on Duncker's (1945) tumor problem.

Organization involves structuring information to facilitate comparison, classification, enumeration, generalization, and cause-effect relationships. Cues that assist the learner in recognizing associations and trends or constructing a coherent mental representation facilitate organization. Using static graphics to represent a dynamic event is particularly challenging (Hegarty, 1992). In such cases, numbers, lines, or arrows (Tversky, et. al., 2008) or spreading color cues (Boucheix & Lowe, 2010) representing temporally spaced events can serve as organization cues.

Integration processes can include the integration spatially separated elements within a single representation or integrating information across multiple representations such graphs and text. Integration cues can aid learners in relating spatially separated elements (Lowe, 1989) or elements across different modalities such as text and graphs using simultaneous flashing (Craig, et. al., 2002), color coding (Kalyuga, et. al, 1999), or graphical organizers (Mautone & Mayer, 2007) can make causal or functional relations explicit and facilitate creation of a situation model (Johnson-Laird, 1983).

Outcome Feedback

One of the important drivers of learning, including representational change, is feedback. The notion of feedback has taken many forms, depending on the historical era, and the associated dominant theoretical frameworks. Early on in American educational research, when the Behaviorist framework dominated, feedback was conceptualized in terms of positive or negative reinforcement. The basic idea underpinning reinforcement is the Law of Effect (Thorndike, 1911) – the intuitive notion that if an action is followed by a satisfactory outcome then the tendency to produce that action is strengthened, namely reinforced.

The role of feedback has been also considered in light of higher-order cognitive processes involved in self-regulated learning. Bangert-Drowns et al. (1991) concluded that feedback “empowers active learners with strategically useful information, thus supporting self-regulation.” The notion of feedback thus evolved from focusing solely on external feedback to also including internal feedback, namely feedback generated by the learner during the process of self-regulation. This notion of feedback was influenced by the work of Meyer (1986), who characterized teachers’ feedback to students, and work by Chinn and Brewer (1993) on conceptual change, who characterized the ways in which students do or do not change their naïve theories in response to feedback provided by anomalous data. In light of this research, Butler and Winne (1995) proposed five functions that feedback could potentially serve in the process of conceptual change, namely, confirmation of correct understanding, addition of needed information, overwriting false information, tuning partial understanding, and restructuring schemata. They expanded on the model by Bangert-Drowns et al. (1991) to integrate instruction, self-regulation, feedback and knowledge construction.

The role of feedback has also been considered in second language learning. A review by Loschky and Harrington (2013) when interpreted in light of Butler and Winne’s (1995) feedback types, shows an important distinction between outcome feedback, which only provides information on correctness of an answer, and elaborated feedback, which also includes follow-up explanations. These studies point to elaborated feedback as most effective, but show that outcome feedback is also effective in promoting initial learning (Carroll, Roberge & Swain, 1992; Carroll & Swain, 1993) and long-term retention (Leow, 2000).

In this study we explore the role of outcome (correctness) feedback, which is akin to creating a discrepant event, thereby causing cognitive dissonance (Festinger, 1957) or disequilibrium (Piaget, 1964), which can lead to knowledge restructuring (i.e., representational change), which has been argued to be the most important type of learning (Rumelhart & Norman, 1976), and is most relevant to our project. Outcome feedback has been shown to invoke conceptual change (Posner, et. al., 1982) and facilitate problem solving (Mory, 2004) in computer-aided instruction (e.g. Fraij, 2010; Martin, et. al, 2002). Importantly, by combining correctness feedback with cueing, the combination can be functionally considered as a form of elaborated feedback.

Research Questions

In a broad sense, this study investigated the influence of visual cueing and outcome feedback on students' problem solving, reasoning, and eye movements while they solved conceptual physics problem. This study was designed to answer the following research questions:

1. How does the combination of short duration visual cues and/or outcome feedback influence students' performance while solving introductory conceptual physics problems?
2. Does problem solving improve on subsequent uncued transfer problems after being provided with visual cues and/or outcome feedback on the training problems?
3. How do visual cueing, outcome feedback, and the combination thereof affect the resources students activate while solving these problems?
4. How does visual cueing affect the learner's visual attention?
 - Among students who demonstrate learning, how does visual attention compare before and after viewing visual cues?
 - How do the eye movements of cued and uncued students compare?

Layout of Dissertation

This dissertation consists of six chapters. In the first chapter, I have discussed the motivation for this research and relevant prior research. Chapter 2 describes the design of the study and eye tracking methodology. The first two research questions are addressed in Chapter 3. The third chapter focuses on the quantitative results describing influence of visual cueing and outcome feedback on students' problem solving performance. The third research question is addressed in the fourth chapter. In Chapter 4, I present a conceptual model describing the function of visual cueing and outcome feedback along with a qualitative analysis of students' reasoning patterns. In Chapter 5, I describe the analysis of the eye movement data to address the final research question. Chapter 6 summarizes how the results described in chapters 3-5 have addressed the research questions and presents implications for future research.

Chapter 2 - Methods

Participants

The participants in this study (N=90, 39 females, 51 males) were enrolled in the same traditional algebra-based physics course at a large, Midwestern university. The students were invited to participate through an email sent to everyone enrolled in the course and were compensated with extra credit.

Materials

Problem Design

Four sets of related problems covering the topics of speed and energy conservation were investigated in this study (see Appendix A for the complete list of problems). The requisite material had been covered in lecture prior to the recruitment of students. The problem sets examined in this study all contained diagrams with features consistent with novice-like answers documented in the literature and separate areas relevant to correctly solving the problem. To solve the problems, it was necessary for students to select relevant information and/or to make the appropriate comparisons across certain features of the diagram. A more detailed explanation of these problems can be found in Madsen *et al.*, 2012.

Problem Sequence

Each set consisted of eight open-ended problems: an initial problem, six isomorphic training problems, and a transfer problem. The problem statements and context provided in the training problems were identical to the initial problem. The training problem diagrams differed from one another in such a way that the correct responses may vary, but the same method would be applied to arrive at the solution. The transfer problem assessed the same concept as the other problems in the set, but had different surface features (e.g. Reed, 1993).

For example, in the problem set shown in Figure 2.1, the steepness and depth of the slopes varied across the initial and training problems. Participants correctly solving these

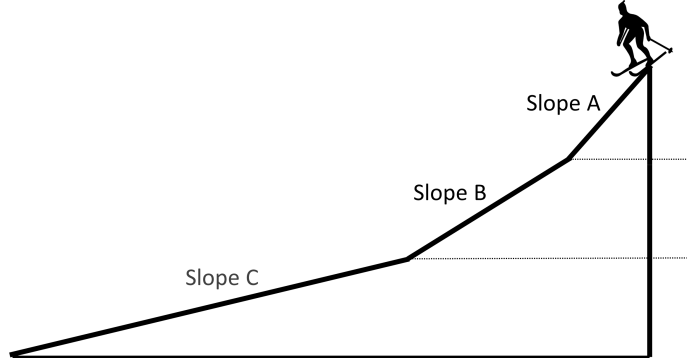
problems would provide explanations in which the sections of the slope would be ranked according to their change in vertical displacement, while the most common incorrect explanation

provided by students would involve the steepness of the slopes. All of the training problems in the Skier problem set would involve similarly designed diagrams in which the heights and slopes would vary but the method necessary to correctly solve the problem would remain unchanged. The same was true for all of the other problem sets investigated in this study.

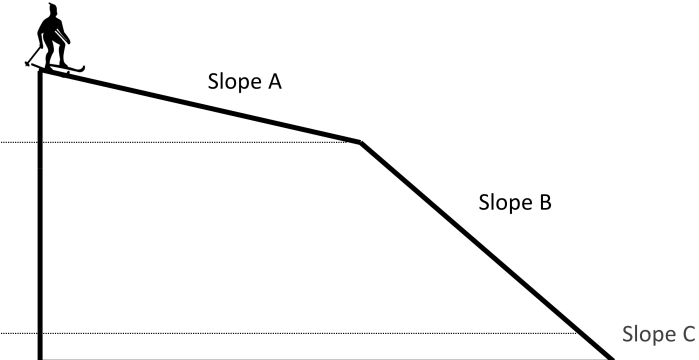
The transfer problems in each set had different surface features, but tested the same concept as the initial and training problems. In the example set shown in Figure 2.1, students were required to rank the change in potential energy for each section of a roller coaster track in which one of the sections had a net change in height of zero. This was not a situation that had been presented to students in earlier problems in the set, but was an extension of the concepts they had applied in previous problems.

Figure 2.1 An example of an initial (top), training (middle), and transfer (problem) from the Skier problem set.

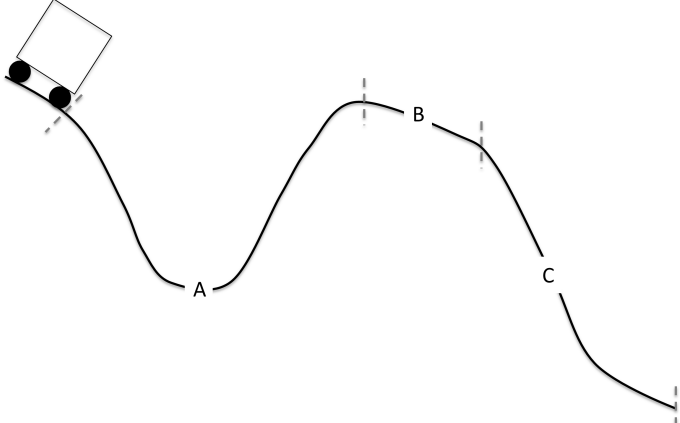
Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (Rank the change in the potential energy not the total value of the potential energy.)



Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (Rank the change in the potential energy not the total value of the potential energy.)



A roller coaster follows a frictionless track. Rank the changes in potential energy of the roller coaster in each section of the track from greatest to least. (Rank the change in the potential energy not the total value of the potential energy.)



Cue Design

Participants in the cued conditions (Cue Only and Cue + Feedback) were shown visual cues overlaid on the diagrams of the training problems. The cues were described to the as hints which were meant to help them solve the problem. To view the cue on the training problems, students pressed a button on the keyboard. All participants in cued conditions were required to view the cue at least once before providing a response, but there was no limit on the number of times they could replay it. Each cue lasted for a total of eight seconds. This duration was chosen as it was the shortest possible amount of time to display the animated cues at a rate of one colored shape per second.

The cues were designed in line with representational change theory to aid students in the selection and integration of the relevant information provided within the diagram which would lead to meaningful elaboration and re-encoding. The cues were pilot tested with a separate cohort of students (N=24) the previous semester to ensure that students' interpretation of the cues was similar to our own. Examples of the cues are provided in Figure 2.2 and are discussed in further detail below.

The cue for the Graph problem set was a set of red tangent lines which appeared along the non-linear curve shown in the graph for the full duration of the cue (8 seconds). These tangent lines aimed to help students to visualize the non-constant slope of the curved line which they could then compare to the slope of the straight line. This served as an integration cue as it could assist the student in making the appropriate comparisons across the representation (comparing the slopes of the two lines). The cue may also serve in elaboration, as the tangent lines add information to and extend the representation by explicitly representing the slope.

Figure 2.2 Examples of training problems with the cue superimposed from the Graph (top), Skier, Ball, and Roller Coaster (bottom) problem sets. All cues appeared on screen for a total of 8s at a time.

The motion of two objects is represented in the graph. When are the two objects moving with the same speed?

Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (Rank the change in the potential energy not the total value of the potential energy.)

Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what time does Ball B have the same speed as Ball A?

How does the final speed of cart A compare to the final speed of cart B if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored.)

The cue for the Skier problem set highlighted the change in heights of each slope as the heights are directly related to the change in potential energy for each slope. The slopes were also deemphasized by changing their color to the lightest gray still visible. This cue served to aid in the selection of the relevant information (the change in height) by enhancing the heights and suppressing the shape of the slopes. Ultimately, this could help the learner to re-encode the problem by replacing the existing representation (shape of the slopes) with a more productive representation (change in heights).

In the Ball problem, it is necessary for students to compare the distances travelled by each ball in a given time interval to determine when the two have the same speed. The cue was designed to help students make the necessary comparisons between the two balls (integration). The spaces between each ball was sequentially highlighted in the order indicated in Figure 2.2. Each yellow rectangle was visible for one second before the next in the sequence appeared. The cue may serve in the process of elaboration by guiding the learner to attend to the information provided in the diagram in a specific order thereby enriching the existing representation.

To correctly solve the Roller Coaster problem, students must compare the initial and final heights of the two carts. The cue sequentially highlighted the initial and final positions of cart A and then repeated the same for cart B, aiding in integration. By guiding the comparison of the relative positions of the carts, the cue can also facilitate selection of the relevant information in diagram (i.e. change in height rather than shape of the track).

Design and Procedure

Each participant took part in an individual session lasting 50-60 minutes, on average. At the beginning of the session, participants were given a short explanation of the goal of the interview and given instructions. The eye tracker was calibrated to the individual using a nine-point calibration and validation procedure, with a threshold agreement of 0.5° visual angle required to begin the experiment. Participants were randomly assigned to one of four conditions: Cue + Feedback (N=22), Cue Only (N=22), Feedback Only (N=24), or Neither (N=22). All participants worked through four problem sets, each containing an initial problem, six isomorphic training problems, and a transfer problem. The order of the problem sets and the training problems within each set was randomized.

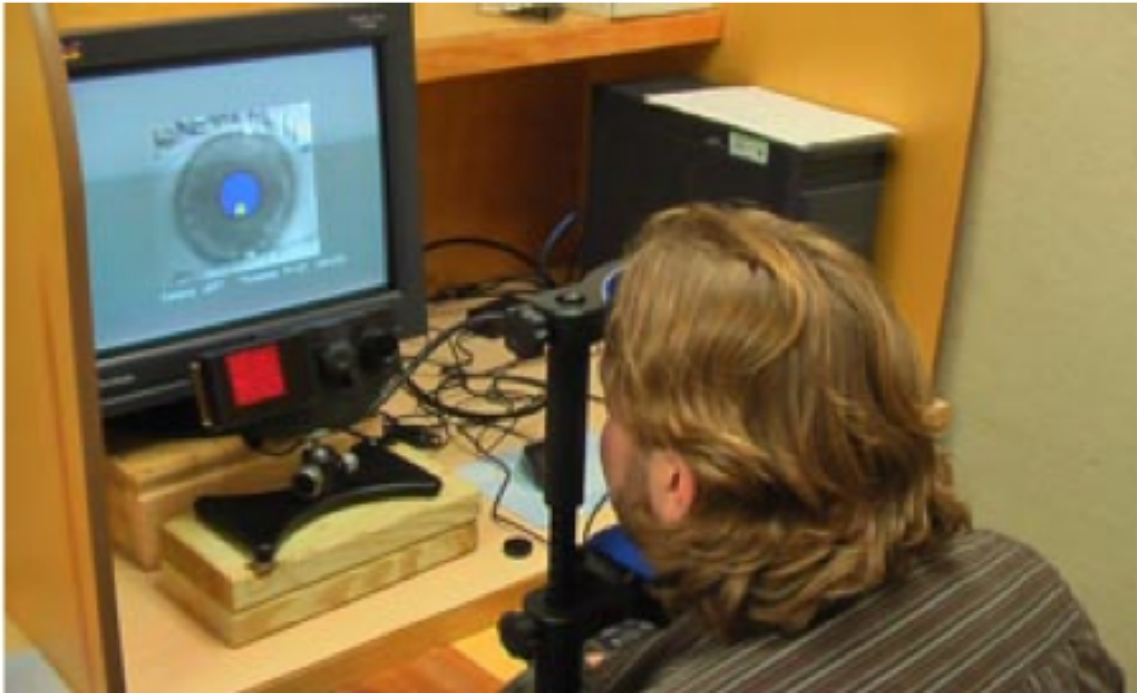
The problems were presented on a computer screen, and students were instructed to spend as much time as they needed on each question and to give a verbal answer and explanation whenever they were ready. The participants were able to point to areas on the computer screen while explaining their answers if necessary. The experimenter used a pre-defined rubric to determine if the given answer and explanation were correct or incorrect. The experimenter would ask for clarification if the participant provided a vague answer or explanation. To be considered correct, the responses were required to contain both the correct answer and scientifically correct explanation.

Those in the cued conditions saw colored shapes superimposed on the diagrams of the training problems for eight seconds at a time, but were not provided with cues on the transfer problem. Students in feedback conditions were told if their responses were correct or incorrect, but were given no additional information. Those receiving feedback were instructed at the beginning of the session that both their answer and explanation had to be correct for their response to be considered correct.

Eye Tracking Technology

Students' eye movements were recorded with an EyeLink 1000 desktop mounted eye-tracking system (<http://www.sr-research.com>), with an accuracy of less than 0.50° of visual angle. The problems were presented to participants on a computer screen with a resolution of 1024 by 768 pixels and a refresh rate of 85 Hz. The images subtended $33.3^\circ \times 25.5^\circ$ of visual angle. Participants used a chin and forehead rest that was 24 inches from the screen. The chin and forehead rest was used minimize extraneous head movements to increase the accuracy of the measurements. An eye movement was classified as a saccade (i.e., in motion) if the eye's acceleration exceeded $8,500^\circ/s^2$ and the velocity exceeded $30^\circ/s$. Otherwise, the eye was considered to be in a fixation (i.e., stationary at a specific spatial location). A nine-point calibration and validation procedure was used at the beginning of the experiment. The eye tracker, chin rest and computer monitor are pictured in Figure 2.3.

Figure 2.3 Participant using the head and chin rest while his eye movements are recorded by the EyeLink 1000 desktop eye tracker (pictured below the monitor).



Chapter 3 - Visual Cueing and Outcome Feedback Improve Problem Solving

Introduction

This study builds on the successful use of implicit visual cues in the work of Thomas & Lleras (2007, 2009) and Madsen et al. (2013) described in Chapter 1. This study extends the work completed in Madsen et al. (2013) in two important ways, both of which improve the ecological validity of the research. First, students who were provided the visual cues were told that the cues were designed to facilitate them in solving the problem. Second, students were provided feedback indicating to them that their solution i.e answer and/or reasoning was incorrect. Both of these changes make the research conditions similar to that of a real online learning environment where students may be provided hints to help them answer questions and feedback to indicate whether their answers are correct or incorrect. The cues were also redesigned and pilot tested with a separate cohort of students prior to the study described here.

Theoretical Background

The function and mechanism of visual cueing can be interpreted through the lens of two theoretical frameworks. The first is Representational Change Theory (Ohlsson, 1992) is related to the cognitive mechanisms involved in solving problems that require insight rather than pure algorithmic calculations. The second is the Framework of Attention Cueing (de Koning et al., 2009) which describes the function and mechanism of visual cueing as it relates to the cognitive mechanisms involved in problem solving. We also draw from the feedback literature (e.g. Butler & Winne, 1995) in providing outcome feedback. These have all been described in greater detail in Chapter 1.

Connections Between Theoretical Background and Current Study

In this study we apply Representational Change Theory to understand the mechanism by which visual cues can facilitate physics problem solving. The problems in this study are conceptual in nature and lend themselves to insight, as they require learners to recognize the appropriate concept and resources (Hammer, 2000) necessary to solve the problem. Once a

student recognizes the appropriate concept to use, they can apply the necessary conceptual resources to quickly arrive at the correct solution. The process does not require going through a long series of mental steps or calculations before getting to an answer.

We have previously observed that students who were incorrect on the first problem in a set of similar problems tended to repeatedly use the same incorrect solution path for every problem in the set. Thus, in terms of Ohlsson's model of insight problem solving (1992) the solvers were apparently not facing an impasse that would force them to restructure their faulty representation of the problem. This points out a difference between many physics problems, including those in the current study, and many common insight problems (e.g. Maier's Two-String Problem (Maier, 1931)). When solving physics problems the learner may not know that they have failed to reach the goal state, while many insight problems are structured in such a way that failure to reach the correct goal state is self-apparent (i.e. the solver cannot generate any solution). We therefore decided to provide the solvers with outcome feedback after they gave their answer to each problem. We hypothesize that this could induce an impasse when the learner attempts to solve the subsequent similar problems, which may result in the learner being receptive to considering previously ignored information. In such cases, the visual cues could direct solvers' attention to relevant information, which could activate previously dormant relevant resources from long-term memory, enabling the solver to create a new representation for the problem that could break the impasse.

We hypothesize that visual cues can serve to help the student mentally re-represent (or restructure) leading to the insight necessary to break the impasse. The purpose of visual cues is to help the student replace an existing unproductive representation with a productive one, or add to their existing representation until it is sufficient to solve the problem. In the current study we explore visual cues that we believe help re-representation occur through elaboration and re-encoding.

In elaboration, the learner gathers additional information to extend their representation. Cues that facilitate the addition of critical new information are typically organization/integration type cues. These help the learner to attend to information in a particular order or to make the appropriate comparisons between different elements of the diagram. A learner attending to the

information provided by these cues may activate previously dormant resources from the long-term memory, allowing them to eventually re-encode a representation for the problem.

Re-encoding involves backtracking through layers of the problem representation, replacing unproductive layers with new productive layers. Selection cues facilitate re-encoding by prompting the learner to suppress irrelevant information and enhance relevant information. The importance of suppression/inhibition of thematically irrelevant information for language comprehension has been shown by Gernsbacher and Faust (1995) and we argue that it is equally important for re-encoding of problem representations. The learner can then ignore the irrelevant information and attend to relevant information, which in turn activates previously inactive resources allowing them to encode a new representation for the problem.

Analysis and Results

Number of Times the Cue was Played

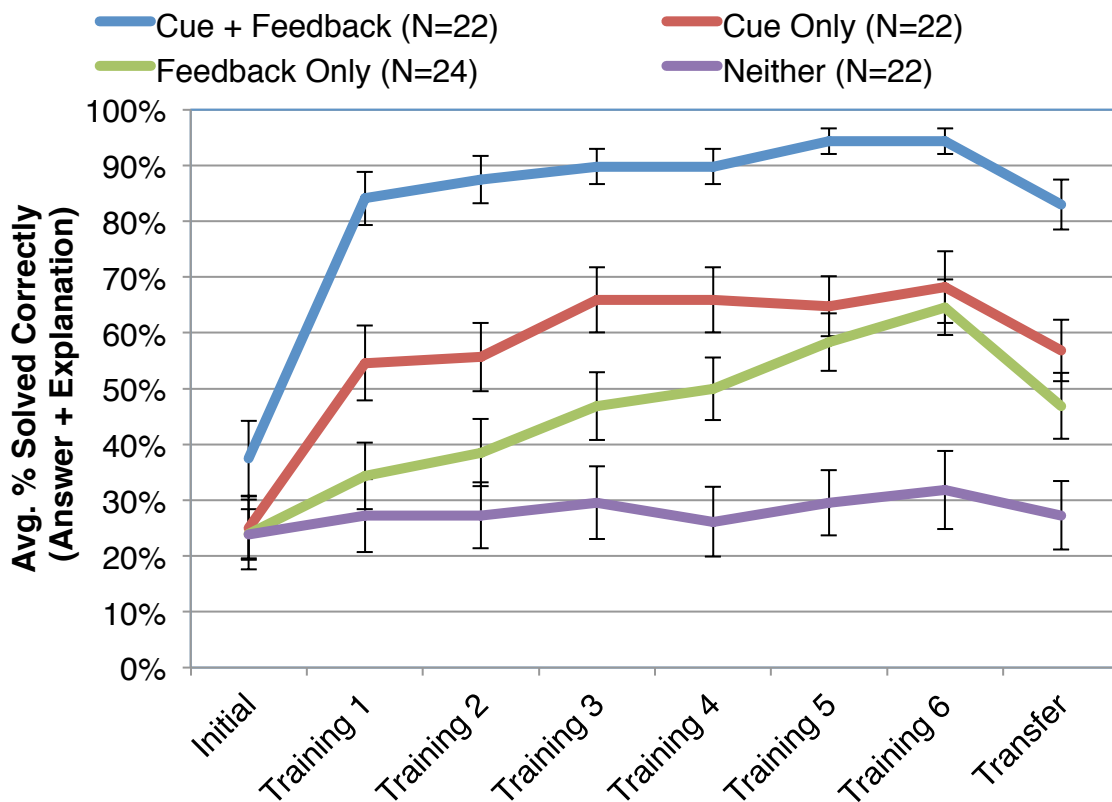
Students in the Cue + Feedback and Cue Only conditions were required to play the cues on the training problems at least once, but were allowed to replay it as many times as desired. However, the majority of the time the students chose to play the cues just once, accounting for 90.9% of all training problems solved. Students rarely played the cue twice or more, occurring in 7.9% and 1.2% of cases, respectively. Multiple viewings of the cue occurred most often while students solved the first training problem presented to them in the set, accounting for 53.7% of multiple viewings. As the order of the training problems was randomized, this result is more likely to be due to the students' first interaction with the cue, rather than the influence of any single training problem in particular.

Overall Problem Solving Performance

We first investigated the overall problem solving performance of participants as they progressed from the initial problem to the transfer problem. To do this, we averaged each participant's performance across the four problem sets for each individual problem within the set. Figure 3.1 shows the performance of each condition from the initial to transfer problem. The Cue + Feedback condition had an average increase in the proportion of problem correctly

solved of 46.6% from the initial problem to the first training problem, which grew by an additional 10.2% by the sixth training problem, with participants correctly solving an average of 94.3% of the last training problems in the sets. The students in the Cue + Feedback group were able to provide correct responses and explanations to an average of 83.0% of the transfer problems.

Figure 3.1 Average student performance averaged across all problem sets. Error bars represent ± 1 std. error of the mean.



The Cue Only group followed a trend similar to the Cue + Feedback group, though with lesser magnitude. After seeing cues on the first training problem, the average proportion of problems solved correctly by students increased by 29.6%. This proportion grew by an additional 13.6% on the final training problem, with students correctly solving an average of 68.2% of sixth

training problems in each set. Participants who saw cues on the six training problems were able to provide a correct response and explanation to an average of 56.8% of transfer problems.

The Feedback Only group exhibited a more gradual increase. After receiving outcome feedback on the initial problem, participants in the Feedback Only group were able to solve an additional 10.4% of first training problems, on average. By the sixth training problem, these students were able to answer an average of 64.5% of the final training problems in the set, an increase of 30.2% from the first training problem. Students who received outcome feedback were able to correctly solve an average of 46.9% of transfer problems. The No Cue + No Feedback group demonstrated static performance, with the average percentage of problems solved correctly remaining between 25% and 30% across all problems in the set.

To statistically compare the performance of each group, we performed a 2x2x8 Repeated Measures ANOVA with cue and feedback as between-groups factors and problem as the within-groups factor. The results are presented in Table 3.1. There were significant main effects of Cue, Feedback, and Problem, such that students did better with cues, better with feedback, and across conditions did better on later training problems. There was no significant interaction between cue and feedback factors, indicating that each had an independent additive effect. However, these main effects were qualified by a pair of significant two-way interactions between cue and problem, and feedback and problem.

Table 3.1 Summary of the results of a Repeated Measures ANOVA comparing the performance of students from the initial to transfer problem. The assumption of sphericity was violated, so a Greenhouse-Geisser correction has been applied to the degrees of freedom for the repeated measures effects. The significance level is $\alpha = .05$.

Effect	ANOVA Result	<i>p</i>	η_p^2
Cue	$F(1, 86) = 51.75$	<.001	.376
Feedback	$F(1, 86) = 21.77$	<.001	.202
Problem	$F(5.6, 481.7) = 47.76$	<.001	.357
Cue*Feedback	$F(1, 86) = 0.72$.399	.008
Cue*Problem	$F(5.6, 481.7) = 10.62$	<.001	.110
Feedback*Problem	$F(5.6, 481.7) = 4.83$	<.001	.053
Cue*Feedback*Problem	$F(5.6, 481.7) = 2.34$.034	.026

Each of these two-way interactions suggest that the effects of both cueing and feedback differed across the problems. These two-way interactions, however, were also qualified by significant three-way interaction between Cue, Feedback, and Problem. To probe this 3-way interaction, we ran four 2-way ANOVAs, to determine whether the Cueing x Problem interaction differed as a function of Feedback, or the Feedback x Problem interaction differed as a function of Cueing, or both.

We ran a first pair of 2-way ANOVAs for Cueing x Problem: one for the Feedback condition, and one for the No Feedback condition, both of which showed significant 2-way interactions between Cueing and Problem. To understand these 2-way interactions, we must start with the effect of problem, which was to show a trajectory of improvement from the initial problem to the transfer problem, namely a learning trajectory. Specifically, when students were given feedback, learning across problems was quite different depending on whether or not there was cueing ($F(5.2, 481.7) = 6.84, p < .001$). With cueing, learning was rapid and stayed high. Without cueing, learning was slow and gradual. Likewise, when students were given no feedback, learning across problems again differed substantially depending on whether or not there was cueing ($F(4.9, 481.7) = 7.52, p < .001$). With cueing they showed relatively rapid learning across problems, but without cueing they did not. Thus, this first pair of 2-way interactions showed important differences in the trajectory of learning across problems as a function of whether there was cueing or not, both with and without feedback.

We then ran a second pair of 2-way ANOVAs for Feedback x Problem: one for the Cueing condition, and the other for the No-cueing condition, only one of which showed a significant two-way interaction, thus explaining the 3-way interaction (i.e., a difference in the 2-way interactions based on a third variable). Specifically, when there was no cueing, there was a significant 2-way interaction between problem and feedback ($F(5.5, 481.7) = 5.81, p < .001$). Namely, in the absence of cueing, if students were given feedback, they showed a gradual learning trajectory across practice problems. However, in the absence of both cueing and feedback, there was no learning across problems. Thus, in the absence of cueing, feedback was necessary to show learning across practice problems. Conversely, when cueing was present, we found no significant 2-way interaction ($F(4.6, 481.7) = 1.90, p = .091$, because we found the same trajectory of learning across problems, namely a rapid increase, in both the feedback and no-

feedback conditions. Thus, when there was cueing, feedback was not necessary for learning across practice problems.

In sum, the 3-way interaction shows that the trajectory of learning across practice problems depended strongly on cueing regardless of feedback, but the same was not true for feedback. Both with and without feedback, there were important differences in the trajectory of learning depending on whether or not there was cueing. Without cueing, feedback was necessary for learning, but with cueing, feedback had no impact on the trajectory of learning across problems.

To further probe the 3-way interaction, in order to determine the precise differences in trajectory of learning, we ran a Repeated Measures ANOVA with Problem as the within-subjects factor for each condition separately using the omnibus mean square error to calculate the F ratios. The results are reported in Table 3.2. As noted above, we found that the No Cue + No Feedback condition, did not have a significant effect of Problem, $F(5.2, 481.7) < 1$. This lack of change in performance as students progressed through the problem set indicates a lack of learning. This is not surprising, as students who were able to solve the initial problem correctly would be able to solve the training problems. Likewise, for those students who incorrectly solved the initial problem, lacking cues or outcome feedback, they would have little reason to change their responses. Thus, many students in the No Cue + No Feedback condition would often respond to problems saying they had the “same answer and same reason” given in the previous problem.

The Cue + Feedback, Cue-Only, and Feedback-Only conditions all had significant main effects of Problem, indicating various learning trajectories as they worked through the problems in the set. To take a deeper look at how student performance improved, repeated contrasts and simple contrasts were performed. Repeated contrasts compare performance on a problem to the one immediately preceding it (e.g., the first training problem vs. the second training problem) and simple contrasts compare each problem to the performance on the initial problem (e.g., the initial problem vs. the sixth training problem).

Table 3.2 Summary of the results of a Repeated Measures ANOVA probing the Cue*Feedback*Problem interaction. The significance level is $\alpha = .004$ after applying a Bonferroni correction for the 13 comparisons made below. The assumption of sphericity was violated, so a Greenhouse-Geisser correction has been applied to the degrees of freedom for the simple main effects.

Effect	Cue + Feedback			Cue Only			Feedback Only		
	Main: $F(3.3, 481.7) = 42.74, p < .001$			Main: $F(4.1, 481.7) = 23.74, p < .001$			Main: $F(5.2, 481.7) = 17.87, p < .001$		
	$F(1, 86)$	p	η_p^2	$F(1, 86)$	p	η_p^2	$F(1, 86)$	p	η_p^2
Initial vs. Training 1	88.44	<.001*	.507	35.56	<.001*	.293	4.81	.031	.053
Initial vs. Training 2	100.00	<.001*	.536	37.65	<.001*	.303	9.27	.003*	.097
Initial vs. Training 3	95.41	<.001*	.526	58.22	<.001*	.405	20.00	<.001*	.189
Initial vs. Training 4	109.29	<.001*	.560	66.95	<.001*	.438	29.60	<.001*	.256
Initial vs. Training 5	107.61	<.001*	.555	52.73	<.001*	.379	42.97	<.001*	.332
Initial vs. Training 6	236.73	<.001*	.566	65.11	<.001*	.430	62.87	<.001*	.421
Initial vs. Transfer	72.143	<.001*	.447	35.35	<.001*	.283	20.00	<.001*	.183
Training 1 vs. Training 2	0.63	.428	.007	0.07	.788	.001	1.02	.315	.053
Training 2 vs. Training 3	0.36	.553	.004	7.42	.008	.080	5.39	.023	.059
Training 3 vs. Training 4	<.01	>.921	<.001	<0.01	>.921	<.001	0.82	.367	.009
Training 4 vs. Training 5	1.73	.192	.020	.12	.735	.001	6.42	.013	.069
Training 5 vs. Training 6	<.01	>.921	<.001	.87	.354	.010	3.13	.080	.035
Training 6 vs. Transfer	5.07	.027	.062	5.07	.027	.062	13.45	<.001*	.135

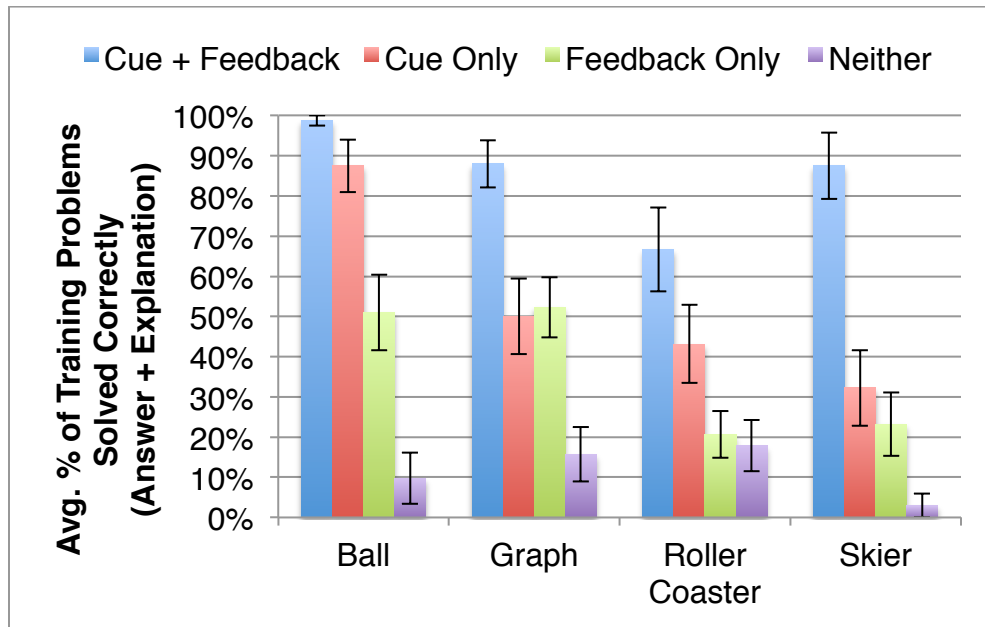
The simple contrasts reveal that students in the Cue-Only and Cue + Feedback conditions perform significantly better on all training and transfer problems compared to the initial problem. This, as noted earlier, shows the predominant effect of cueing on learning across problems. The Feedback-Only condition showed a more gradual trajectory of learning, with no significant difference in the performance between the initial problem and first training problem (when taking into account the Bonferroni corrected alpha level of .004 based on the number of contrasts). Comparing the effect sizes for all three groups reveals that the Cue + Feedback group showed the strongest improvement over the initial problem. In comparing the gains from the initial problem to the transfer problem, the effect size for the Cue + Feedback condition is a factor of 1.6 times larger than the Cue-Only group, and more than double that of the Feedback-Only group.

In examining the repeated contrasts, we find that the Cue + Feedback and Cue-Only groups experienced a significant increase from the initial problem to the first training problem. This suggests that just one instance of seeing cues or receiving both cues and outcome feedback is enough to produce a significant increase in the percentage of problems correctly solved by students in each condition. Comparing the effect sizes for the Cue + Feedback and Cue-Only groups, we see that the Cue + Feedback group has a stronger increase from the initial to the first training problem with nearly double the value of partial eta squared. The remainder of the repeated contrasts for the two cued groups were non-significant, indicating that the increases from one training problem to the next were subtle. Interestingly, both groups showed a non-significant decline between the sixth training problem and the transfer problem. Cues were not provided on any of the transfer problems, yet we did not observe a significant decline in the average proportion of problems correctly solved by students in the cued conditions. The repeated contrasts for the Feedback-Only condition reveals that none of the individual gains from one problem to the next were significant, consistent with the gradual average increase in accuracy from one problem to the next. The group also showed a significant decline from the sixth training problem to the transfer problem, unlike the two groups which were provided with cues. Thus, the learning that students gained from outcome feedback only was not as firmly established as that gained by students who had seen cues.

Training Problem Performance by Problem Set

We next investigated student performance on the training problems for each individual problem set. Because we are interested in the effects of cueing and feedback on learning, for this analysis, we considered only those students who provided incorrect responses to the initial problem in each set—we excluded those students who were able to correctly solve the initial problems because they would also be expected to correctly solve the training problems, and thus not show learning. Figure 3.2 shows the average percentage of training problems that were solved correctly by students in each condition on each of the four problem sets.

Figure 3.2 Average student performance on the training problems. Only those who were unable to correctly solve the initial problem are included in this graph. The error bars represent ± 1 std. error of the mean.



A similar pattern emerged for each of the four problem sets. The Cue + Feedback group was able to correctly solve the largest proportion of training problems in each of the four sets followed by the Cue Only, Feedback Only, and No Cue + No Feedback groups, respectively. Among students who provided incorrect responses to the initial problem, the performance students in the Cue + Feedback group was quite high, correctly solving upwards of 67% of training problems, on average. In the case of the Ball problem, the average percentage of training problems correctly solved by these students reached 98.7%. By contrast, students who provided

incorrect responses to the initial problem in the Ball problem set, but received neither cues nor feedback answered an average 9.8% of training problems correctly.

After filtering out students who answered the initial problem correctly, there were too few students left to run an ANOVA to compare the average percentage of training problems solved correctly by problem set. Thus, a Chi-square test was chosen to compare the performance of each condition for each problem set. The Chi-square test is employed to analyze the frequencies of categorical data and can handle small sample sizes. The performance of the students was analyzed by comparing the number of training problems answered correctly by students in each condition for each problem set. The results of the Chi-square tests are reported in Table 3.3.

The results of the Chi-square tests indicate that for all problem sets the students in Cue + Feedback group were able to correctly solve the significantly highest number of training problems while the No Cue + No Feedback group had the significantly lowest performance. In the case of the Ball problem, the performance of the Cue Only condition was comparable to the Cue + Feedback group and was significantly higher than the Feedback Only and No Cue + No Feedback groups. On the Roller Coaster Problem, the Feedback Only condition performed similarly to the No Cue + No Feedback group, and thus their performance was significantly lower than the Cue + Feedback and Cue Only groups. Together, these results indicate that across all problems tested, the combination of visual cueing and correctness feedback helped students correctly solve and reason about problems which they previously were unable to solve. Importantly, while there were some minor differences between problem sets in the exact pattern of results across the four conditions, overall, the patterns were relatively similar. Thus, the overall pattern of results was not specific a particular problem set, but instead was more general.

Table 3.2 Summary of the results of a Chi-square test comparing the numbers of training problems solved correctly by participants in the four conditions. This analysis only considers students who were unable to correctly solve the initial problem in each set. The significance level is $\alpha = .05$. Cells contributing to the significant difference, as determined by the adjusted residuals (Haberman, 1973), are marked with *.

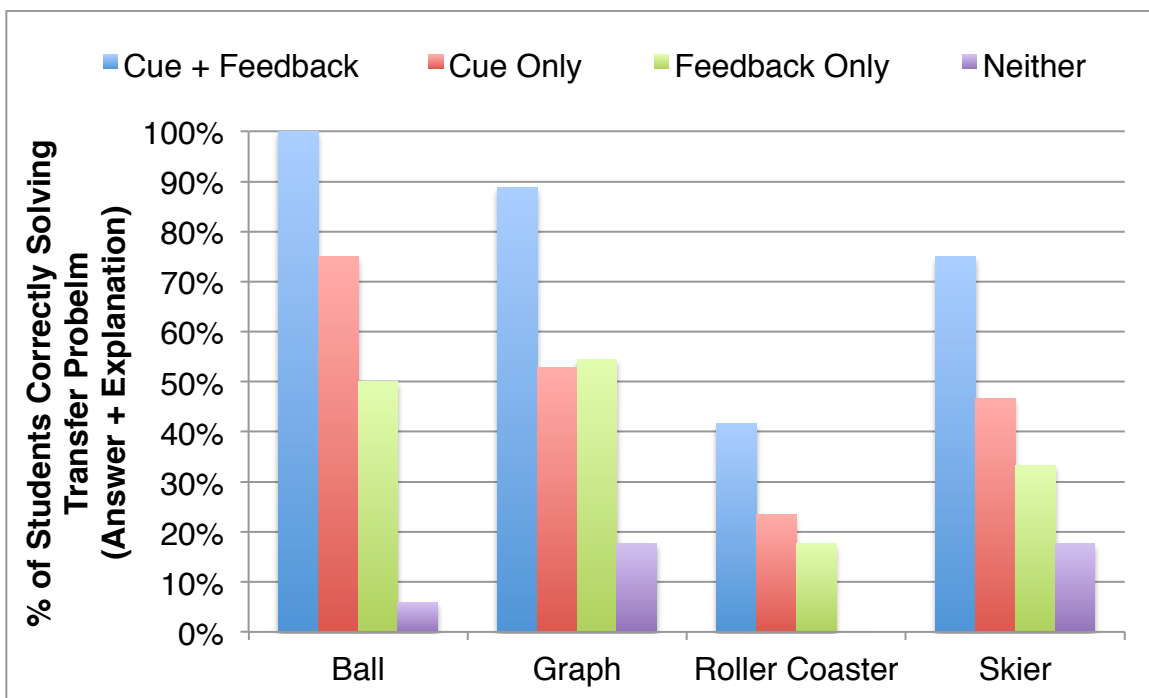
Problem Set	Condition	# of Training	# of Training	Chi-square Result
		Prob. Solved Correctly	Prob. Solved Incorrectly	
Ball	Cue + Feedback ($n = 13$)*	77	1	$\chi^2(3) = 187.86,$ $p < .001, V = .711$
	Cue Only ($n = 16$)*	84	12	
	Feedback Only ($n = 16$)	49	47	
	No Cue + No Feedback ($n = 17$)*	10	92	
Graph	Cue + Feedback ($n = 18$)*	95	13	$\chi^2(3) = 110.102$ $p < .001, V = .498$
	Cue Only ($n = 17$)	51	51	
	Feedback Only ($n = 22$)	69	63	
	No Cue + No Feedback ($n = 17$)*	16	86	
Roller Coaster	Cue + Feedback ($n = 12$)*	48	24	$\chi^2(3) = 54.43,$ $p < .001, V = .389$
	Cue Only ($n = 17$)	44	58	
	Feedback Only ($n = 17$)*	21	81	
Skier	No Cue + No Feedback ($n = 14$)*	15	69	$\chi^2(3) = 144.77$ $p < .001, V = .624$
	Cue + Feedback ($n = 12$)*	63	9	
	Cue Only ($n = 15$)	29	61	
	Feedback Only ($n = 18$)	25	83	
	No Cue + No Feedback ($n = 17$)*	3	99	

Transfer Problem Performance by Problem Set

Thus far, we have demonstrated that the combination of visual cues and outcome feedback has helped students give correct answers and reason about problems which they were previously unable to correctly solve. While this is certainly a promising result, the evidence for learning would be stronger if we could demonstrate that students can subsequently solve a

conceptually related problem having different surface features without the aid of visual cues. To investigate this possibility, we analyzed the transfer problem performance of students on each of the four problem sets. In this analysis, we once again consider only those students who provided incorrect responses to the initial problem in the set. The percentage of students in each condition who were able to provide correct answers and explanations to the transfer problems (after providing incorrect responses to the initial problem) is shown in Figure 3.3.

Figure 3.3 Student performance on the transfer problem. Only those who were unable to correctly solve the associated initial problem are included in this graph.



The trends in the transfer problem performance depicted in Fig. 5 are similar to those observed on the training problem performance displayed in Fig. 4. Once again, students who saw cues on the training problems (but not the transfer problem) and were told if their responses were correct were the highest performing group on each problem set. The Cue + Feedback group outperformed the Cue Only group by an amount ranging from 18.2% (Roller Coaster) up to 36.0% (Graph). A Chi-square test was performed to test if the difference in the number of students who answered the transfer problem correctly in each condition was statistically significant. The results are provided in Table 3.4.

Table 3.3 Summary of the results of a Chi-square test comparing the numbers of students who did and did not correctly solve the transfer problem in the four conditions. Fisher's Exact Test is reported for tests marked with † as a result of an expected cell count being <5. This analysis only considers students who were unable to correctly solve the initial problem in each set. The significance level $\alpha = .05$. Cells contributing to the significant difference, as determined by the adjusted residuals (Haberman, 1973), are marked with *.

Problem Set	Condition	Correctly Solved Transfer Prob.	Incorrectly Solved Transfer Prob.	Chi-square Result
Ball	Cue + Feedback ($n = 13$)*	13	0	
	Cue Only ($n = 16$)	12	4	$\chi^2(3) = 30.26,$
	Feedback Only ($n = 16$)	8	5	$p < .001, V = .716$
	No Cue + No Feedback ($n = 17$)*	1	16	
Graph	Cue + Feedback ($n = 18$)*	16	2	
	Cue Only ($n = 17$)	9	8	$\chi^2(3) = 17.88,$
	Feedback Only ($n = 22$)	12	10	$p < .001, V = .492$
	No Cue + No Feedback ($n = 17$)*	3	14	
Roller Coaster	Cue + Feedback ($n = 12$)*	5	7	
	Cue Only ($n = 17$)	4	13	$\chi^2(3) = 7.28,$
	Feedback Only ($n = 17$)	3	14	$p = .055, V = .347^\dagger$
Skier	No Cue + No Feedback ($n = 14$)*	0	14	
	Cue + Feedback ($n = 12$)*	9	3	
	Cue Only ($n = 15$)	7	8	$\chi^2(3) = 10.01,$
	Feedback Only ($n = 18$)	6	12	$p = .018, V = .407^\dagger$
	No Cue + No Feedback ($n = 17$)*	3	14	

The results of the Chi-square test indicate that there was a statistically significant difference in the performance of students in the four conditions for three of the four problem sets (Ball, Graph, and Skier). In all cases, students in the Cue + Feedback condition were the significantly highest performing, while those in the No Cue + No Feedback condition were the significantly lowest performing. The percentage of students in the Cue + Feedback condition

who were able to provide a correct answer and explanation to the transfer problems in the Ball, Graph, and Skier problems was 100%, 89.9%, and 75%, respectively.

The Roller Coaster problem did not produce a significant result at the $\alpha = .05$ level, but could be considered marginally significant as $p = .055$. Slightly less than half of the students in the Cue + Feedback condition who provided incorrect responses to the initial problem in the set were able to correctly solve the uncued transfer problem after working through the training problems. However, not a single one of the 17 students in the No Cue + No Feedback condition were able to correctly answer the transfer problem after incorrectly solving the initial problem.

Discussion and Conclusions

In this study we investigated the effects of visual cueing and outcome feedback on physics problem solving. We found clear evidence to suggest that the combination of visual cueing and outcome feedback was effective helping students provide correct responses and explanations to problems they were previously unable to solve (training problems). We found significantly more students changed to a correct response after seeing visual cues and receiving outcome feedback on all four problems investigated. From an educational standpoint, it is not sufficient that visual cues can help students only for those problems that contain cues. Therefore we had students solve a related physics problem with different surface features without the help of cues at the end of each set. After filtering out students who were initially able to solve the problem, we found that significantly more students who saw visual cues and received outcome feedback were able to provide a correct answer and explanation to the transfer problem than students in the other conditions for three of the four problems tested. We found a nearly significant difference on the roller coaster problem.

Through the lens of representational change theory, these results suggest that visual cues may have helped students to re-represent the problems in a productive way through elaboration and re-encoding. The combination of visual cueing and correctness feedback produced the most successful problem solving performance among the participants in this study. Once students in the Cue + Feedback condition learned that their response was incorrect, they likely reached an impasse on the subsequent problem in the set. The visual cues could then help the student overcome the impasse and solve the problems correctly.

This work significantly builds on and extends the results reported in Madsen *et al.* 2013. By informing students of the purpose of the cue and by providing them with outcome feedback, we have increased the ecological validity of the design. We have also redesigned the cues in line with representational change theory to aid the learner in selecting the relevant information provided in problem diagrams, or by leading them to make the appropriate comparisons. This research adds to a growing body of work in physics education on the importance of visual attention in problem solving (Rosengrant et al., 2009; Fiel & Mestre, 2010; Smith et al., 2010; Tai et al., 2006; Madsen et al., 2013). We find evidence to suggest that visual cues combined with outcome feedback can be an effective tool helping students correctly solve and reason about physics problems.

Chapter 4 - The Effect of Visual Cueing and Outcome Feedback on Students' Reasoning

Introduction

In this chapter, we propose a conceptual model that describes the roles of visual cueing and outcome feedback in physics problem solving. The model integrates concepts from Representational Change Theory (Ohlsson, 1992) and the Framework of Attention Cueing (de Koning, 2009) that builds on Mayer's Cognitive Theory of Multimedia (Mayer, 2001). We also draw from previous research and theory on outcome feedback (Butler & Winner, 1995). The theoretical basis for our model has been described in Chapter 1. We present data illustrating how students progress through the proposed model as they solve conceptual physics problems. To show this we will explore one problem set using enhancement cues and one using elaboration cues, respectively referred to as the Skier and Roller Coaster sets, in detail. More specifically we seek to understand how visual cueing, outcome feedback, and the combination thereof affects the resources students activate while solving these problems.

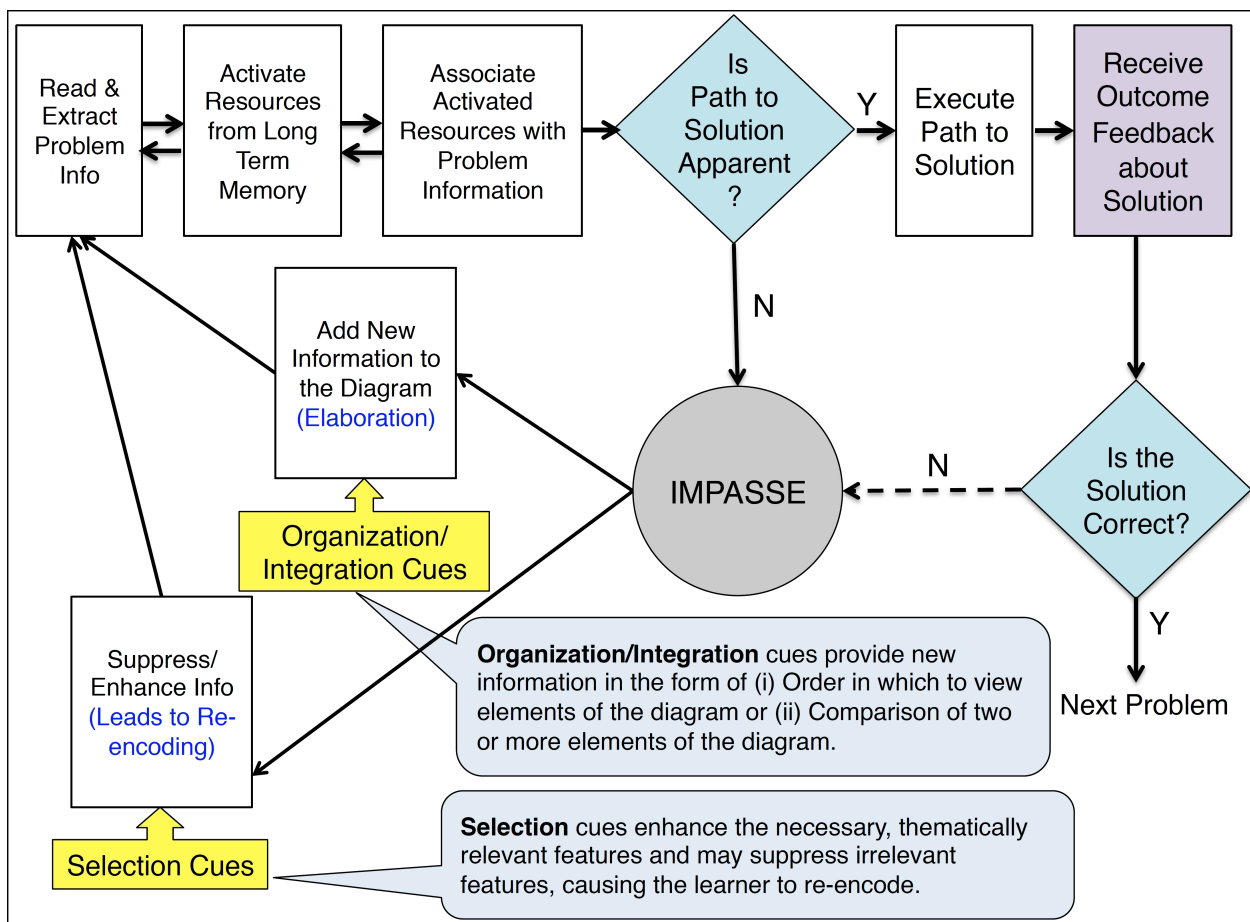
The Model

The model describes the steps needed to solve an insight problem and is shown in Figure 4.1. According to Representational Change Theory, the learner first reads and extracts the problem information, based on which he or she activates the relevant prior knowledge from long-term memory. In a Resources view of knowledge, the learner is activating the conceptual resources relevant (in the solver's mind) to solving the problem (Hammer, 2000). These resources are associated with the problem information. The solution path becomes apparent to the learner, and the solution strategy is executed. After providing a solution to the problem, the learner receives outcome feedback on the correctness of the response, but no further information is provided. Next a similar, isomorphic problem is presented to the learner.

In the event that that a solution path is not apparent to the learner, he or she is then at an impasse in which all problem solving ceases. Another possible path to an impasse is through outcome feedback. When solving physics problems the learner may not know that they have

failed to reach the goal state, while many classical insight problems (e.g. Two String Problem (Maier, 1931) or Nine Dot Problem (Scheerer, 1963)) are structured in such a way that failure to reach the correct goal state is self-apparent (i.e. the solver cannot generate any solution). We therefore decided to provide the solvers with correctness feedback after they gave their answer to each problem. We hypothesize that this could induce an impasse when the learner attempts to solve the subsequent similar problems.

Figure 4.1 Conceptual model describing the process of solving insight problems which integrates elements of Representational Change Theory (Ohlsson, 1992), Framework of Attention Cueing (de Koning, 2009), and Outcome Feedback (Butler & Winne, 1995).



Ohlsson discusses three possible mechanisms to break impasse: elaboration, re-encoding, or constraint removal. The latter lifts previous unnecessary constraints owing to incorrect assumptions or inappropriate ontological categorization (Chi et al., 1981). These kinds of

problems are not amenable to visual cueing. We hypothesize that visual cues can facilitate students' re-representation of a problem in their mind, leading to the necessary insight to break the impasse. The purpose of visual cues is to help the learner to replace an existing unproductive representation with a productive one, or add to their existing representation until it is sufficient to solve the problem. We explore visual cues that we believe help re-representation occur through elaboration and re-encoding.

When a solver gathers insufficient information from the problem to form a coherent representation, the solution may not be apparent, causing an impasse. Cues that facilitate the addition of critical new information (elaboration) are typically organization/integration type cues. These help the learner (i) attend to information in a particular order or (ii) make comparisons between different elements of the diagram. A learner attending to the information provided by these cues may activate previously dormant conceptual resources from long-term memory and eventually allowing them to successfully re-represent the problem.

Re-encoding involves backtracking through layers of the problem representation, replacing unproductive layers with new productive layers. Selection cues can facilitate re-encoding by prompting the solver to suppress irrelevant and/or enhance relevant information. The importance of suppression of thematically irrelevant information for language comprehension has been shown by Gernsbacher and Faust (1995) and we argue that it is equally important for re-encoding of problem representations. The learner then ignores irrelevant information and attends to relevant information, which in turn activates previously inactive conceptual resources from long-term memory and they encode a new representation for the problem.

Examples of enhancement and elaboration cues are provided in Figure 4.2. The enhancement cue superimposed on the Skier problem highlighted the change in heights of each while the slopes were deemphasized by changing their color to the lightest gray still visible. The cue served to aid in the selection of the relevant information, namely the change in height by enhancing the heights and suppressing the shape of the slopes which often relates. Ultimately, this could help the learner to re-encode the problem by replacing the existing representation (shape of the slopes) with a more productive representation (change in heights). An example of

an elaboration cue is superimposed over the Roller Coaster problem shown in Figure 4.2. To correctly solve this problem, students must compare the initial and final heights of the two carts. The cue sequentially highlighted the initial and final positions of cart A and then repeated the same for cart B. By guiding the comparison of the relative heights of the carts, the cue can facilitate in adding the necessary information that may lead students to activate the relevant conceptual resources.

Figure 4.2 Examples of a enhancement cue (top) and elaboration cue (bottom). The red numbers indicate the order in which the yellow boxes appeared on the screen. These numbers were not visible to the students.

Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (Rank the change in potential energy; not the total value of potential energy.)

How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)

Analysis & Results

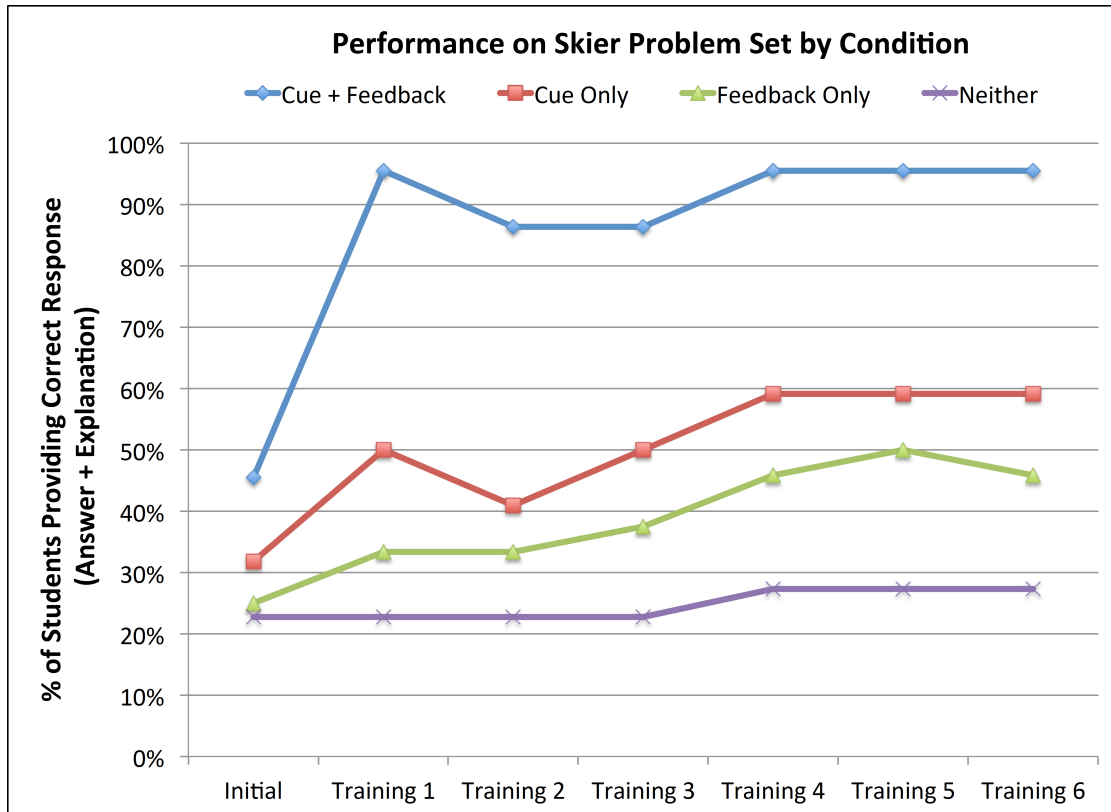
To investigate the reasoning patterns used by students, their responses to the initial and training problems were coded using a phenomenographical approach (Marton, 1986). Two independent researchers transcribed 20% of the interviews before meeting to discuss the themes which emerged from the data. A list of codes was decided upon by the researchers before being applied to the interview data. Inter-rater reliability was established to be 93%.

Enhancement Cues

Performance

Student performance on the Skier problem set is shown in Figure 4.3. We find that 95% of students who were provided with visual cues and outcome feedback were able to solve the final training problem set. This amounted to a 50% increase compared to the initial problem, which is nearly double the improvement exhibited by Cue Only group (27%). Comparing the groups performance on the initial problem, we found no significant difference in the number of students in each condition who answered the initial problem correctly, $\chi^2(3)=3.26$, $p=.374$. However, a significantly larger number of students in the Cue + Feedback condition were able to provide a correct answer and explanation to the final training problem, $\chi^2(3)=22.42$, $p<.001$, $V=.499$.

Figure 4.3 The performance of students in each of the four conditions on the Skier problem set.



Number of Explanations Provided

While the data presented in Figure 4.3 shows that problem solving improved, it does not reveal how students’ patterns of reasoning evolved throughout the set. The number of unique explanations provided by students in each condition is summarized in Table 4.1. We found that students in the Cue + Feedback condition provided the smallest number of unique responses, while those in the Feedback Only condition provided the largest. The results of a One-Way ANOVA revealed that these two groups differed significantly from one another, but no other comparisons between the groups were significantly different. From Figure 4.3, we can see that nearly all students who saw cues and received feedback were able to provide a correct answer and explanation for the first training problem in the set, and therefore would have been unlikely to change their responses on later problems in the set.

Table 4.1 Average number of unique explanations provided by students in each condition while working through the Skier problem set, which had enhancement cues. The results were compared using a One-Way Analysis of Variance

Condition	# of Unique Explanations Mean \pm Std. Error	ANOVA Result
Cue + Feedback	1.64 \pm 0.18	$F(3, 86) = 5.16, p=.003$
Cue Only	2.45 \pm 0.29	
Feedback Only	3.17 \pm 0.35	
Neither	2.45 \pm 0.24	

Most Common Explanations

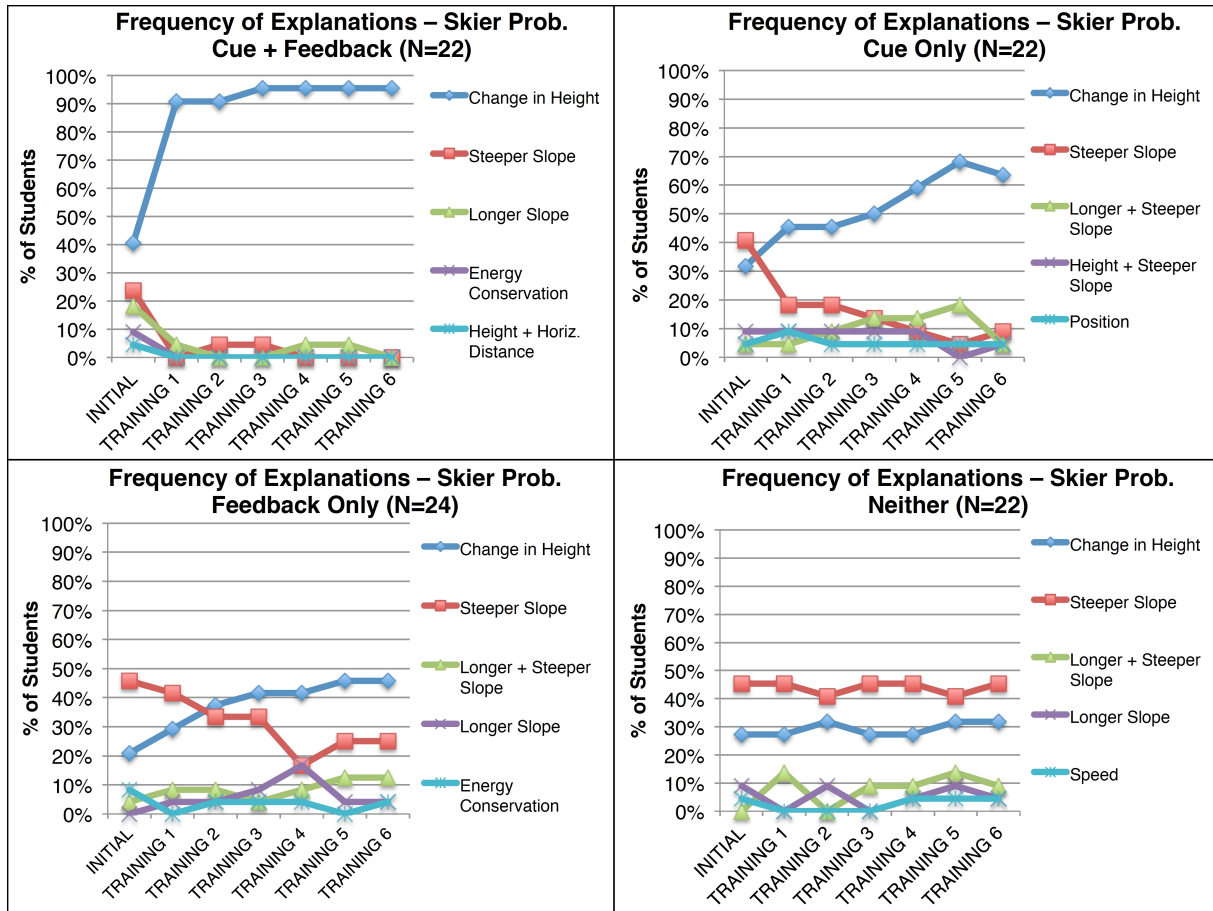
Overall, we observed that students in the Cue Only and Feedback Only conditions exhibited a larger number of unique reasoning patterns while working through the problem sets. Students in the Cue + Feedback group often were able to provide a correct solution within the first two training problems, while those who did not receive cues or feedback often would provide the same explanation to all problems in a given set. The most common explanations provided by students in each condition are summarized in Table 4.2 and Figure 4.4 shows how student responses evolved over time.

Many of the explanations provided by students were similar across the four conditions, such as change in height, steepness of the slope, and length of the slope. We found that many students who either saw cues or received feedback (but not both) would progress through a series of transition states before providing a correct response. Students often combined the steepness of the slope (the most common answer on the initial problem) with another feature such as the change in height or the length along the slope. After receiving feedback on the initial problem and being subsequently provided with visual cues on the first training problem, students in the Cue + Feedback group are immediately able to provide the correct answer and explanation. Those who were not provided with cues or feedback often retained the same response throughout the entire problem set, as can be seen by the relatively flat lines in Figure 4.4.

Table 4.2 Summary of the most common explanations provided by students while solving the Skier problem. The inter-rater reliability was 93%.

Resource	Explanation	Frequency
Change in Height	Change in potential energy = change in height	51.6%
Steeper Slope	Steeper slopes = greater change in potential energy	24.0%
Longer + Steeper Slope	Lengthier and steeper slopes = greater change in potential energy	6.5%
Longer Slope	Lengthier slopes = greater change in potential energy	4.0%
Height + Steeper Slope	Greater change in height + steeper slope = greater change in potential energy	1.8%
Height + Horiz. Distance	Greater change in height and horizontal distance = greater change in potential energy	1.6%
Energy Conservation	The bottom slope always has the greatest change in potential energy because the skier has converted all of his energy into kinetic energy	1.3%
Position	Higher position = greater change in potential energy (Always uses the ranking $A > B > C$)	1.3%
Speed	Greatest change in potential energy when the skier moves the “fastest” (when the slope is steepest, but the student makes no reference to the steepness)	0.6%

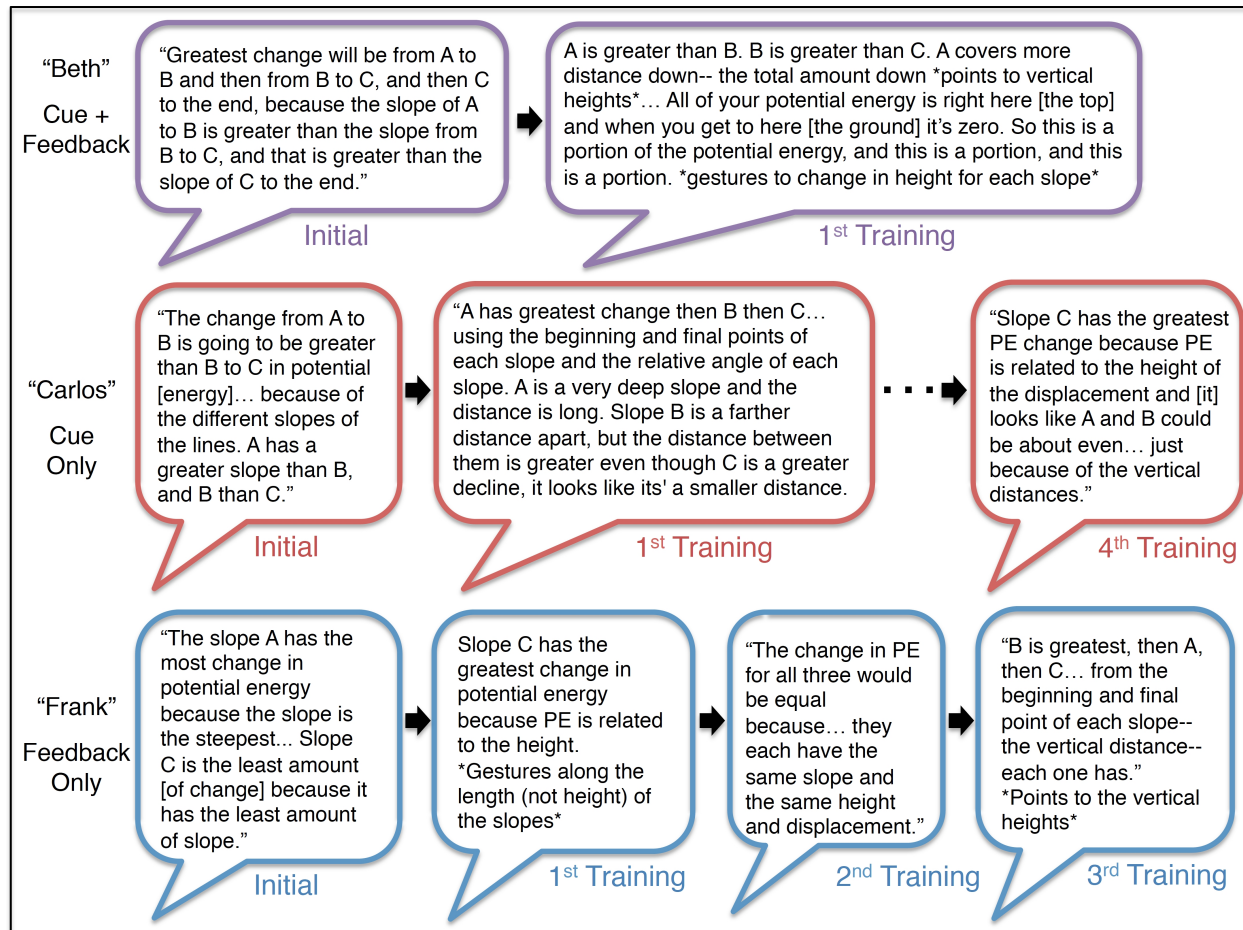
Figure 4.4 Evolution of student responses over time. The five most common responses provided by students in each condition are shown in each of the graphs below.



Examples of Student Responses

To better understand how students’ activation of resources changed as they progressed through the problem set, we present transcribed responses for three students – one who was provided with both cues and feedback (“Beth”), one who was provided with cues only (“Carlos”), and one who was given feedback only (“Frank”). Each of these students provided incorrect responses to the initial problem, citing the most commonly used incorrect explanation. However, at some point during the problem set, the students were able to switch to a correct response and continue to provide correct responses throughout the remainder of the set. The evolution of their responses as they switched from an incorrect to correct responses is summarized in Figure 4.5.

Figure 4.5 Evolution of student responses on the Skier problem from incorrect to correct



After seeing the cue on the first training problem, many students in the Cue + Feedback group were able to provide a correct solution to the problem, including Beth. Beth originally used the steepness of the slopes to compare the change in potential energy. After learning that her response was incorrect, she moved on to the first training problem in the set and was provided with a cue that highlighted the vertical distance beneath the skier. When explaining her response to the first training problem, Beth gestured to the vertical segment of each slope and explained that each represented a portion of the total potential energy in the system. She continued to use a similar method throughout the remainder of the problem set.

Students in the Cue Only condition often would incorporate the change in the height into their answer by combining it with their response to the initial problem. Carlos transitioned through a period of using both the change in height as well as the steepness of the slopes. Like

Beth, he initially ranked the skier's change in potential energy by the steepness of the slopes. However, he was not told that his response was incorrect. Carlos was provided with visual cues on the training problems (described to him as a "hint"). While explaining his answers to the first three training problems, Carlos cited both the steepness of the slopes and the vertical distance traveled by the skier as the influential factors in determining the skier's change in potential energy. However, on the fourth training problem, Carlos explained that the change in potential energy depended only on the change in height and was able to answer the remaining problems in the set correctly.

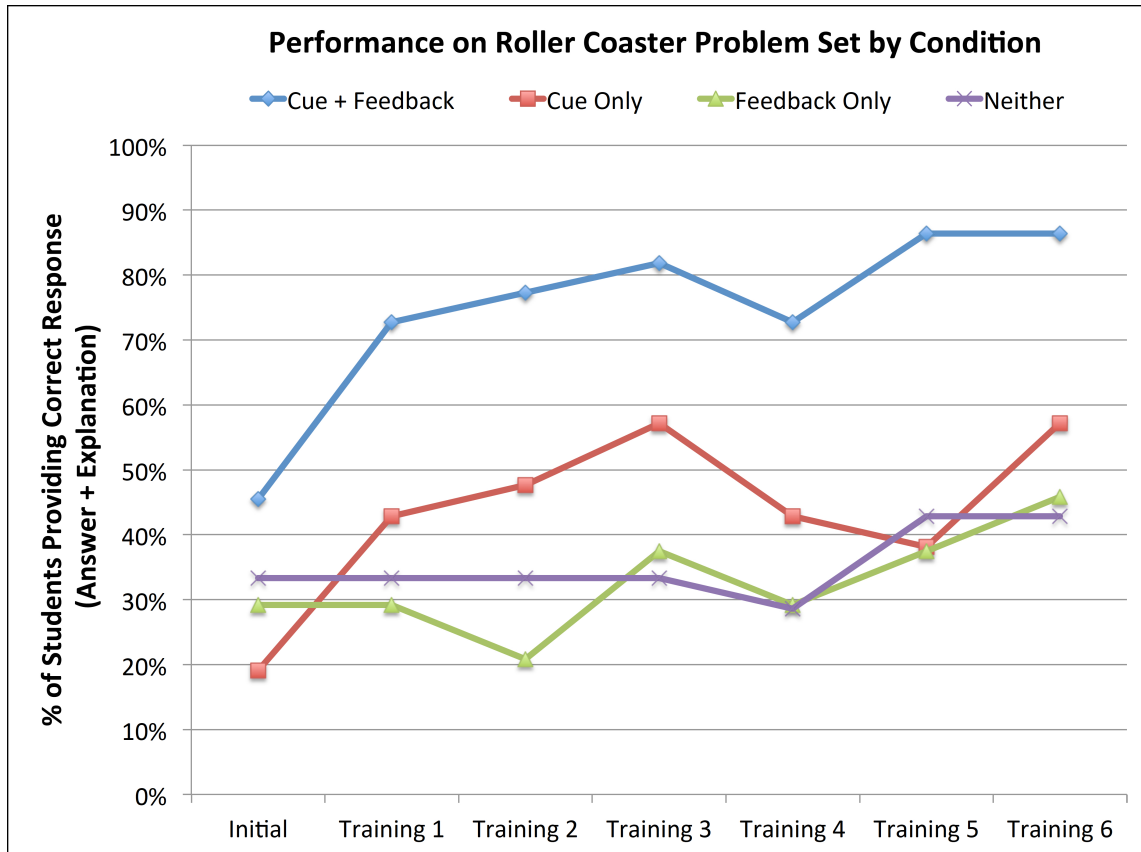
Those in the Feedback Only condition often provided several different explanations as they worked their way through the problem set. For example, Frank provided the same response as Beth and Carlos to the initial problem. He was informed that his response was incorrect, indicating that either his answer, explanation, or both contained an error. Without the cue to provide guidance to the relevant features, Carlos Feedback only condition switched between several explanations (including length of the slopes, combination of the steepness and height) until he settled on the correct solution on the third training problem in the set.

Elaboration Cues

Performance

Student performance on the Roller Coaster problem set is shown in Figure 4.6. The trajectory of the Cue + Feedback group is similar to the one We found that 86% of students who were provided with visual cues and outcome feedback were able to solve the final training problem set. This amounted to a 40% increase compared to the initial problem. There was no significant difference in student performance on the initial problem, $\chi^2(3)=3.56$, $p=.314$. A significantly larger number of students in the Cue + Feedback condition were able to provide a correct answer and explanation to the final training problem, $\chi^2(3)=22.42$, $p=.009$, $V=.356$.

Figure 4.6 The performance of students in each of the four conditions on the Skier problem set.



Number of Explanations Provided

The number of unique explanations provided by students in each condition is summarized in Table 4.3. While the number are a bit larger than those reported for the Skier problem, we find a very similar pattern. Once again, we found that students in the Cue + Feedback condition provided the smallest number of unique responses, while those in the Feedback Only condition provided the largest. The Cue + Feedback group provided a significantly smaller number of unique responses than those who received feedback only or nothing at all.

Table 4.3 Average number of unique explanations provided by students in each condition while solving the Roller Coaster problem, which had elaboration cues. The results were compared using a One-Way Analysis of Variance.

Condition	# of Unique Explanations Mean \pm Std. Error	ANOVA Result
Cue + Feedback	2.32 \pm 0.30	$F(3, 84) = 6.01, p < .001$
Cue Only	3.33 \pm 0.27	
Feedback Only	4.00 \pm 0.36	
Neither	3.42 \pm 0.34	

Most Common Explanations

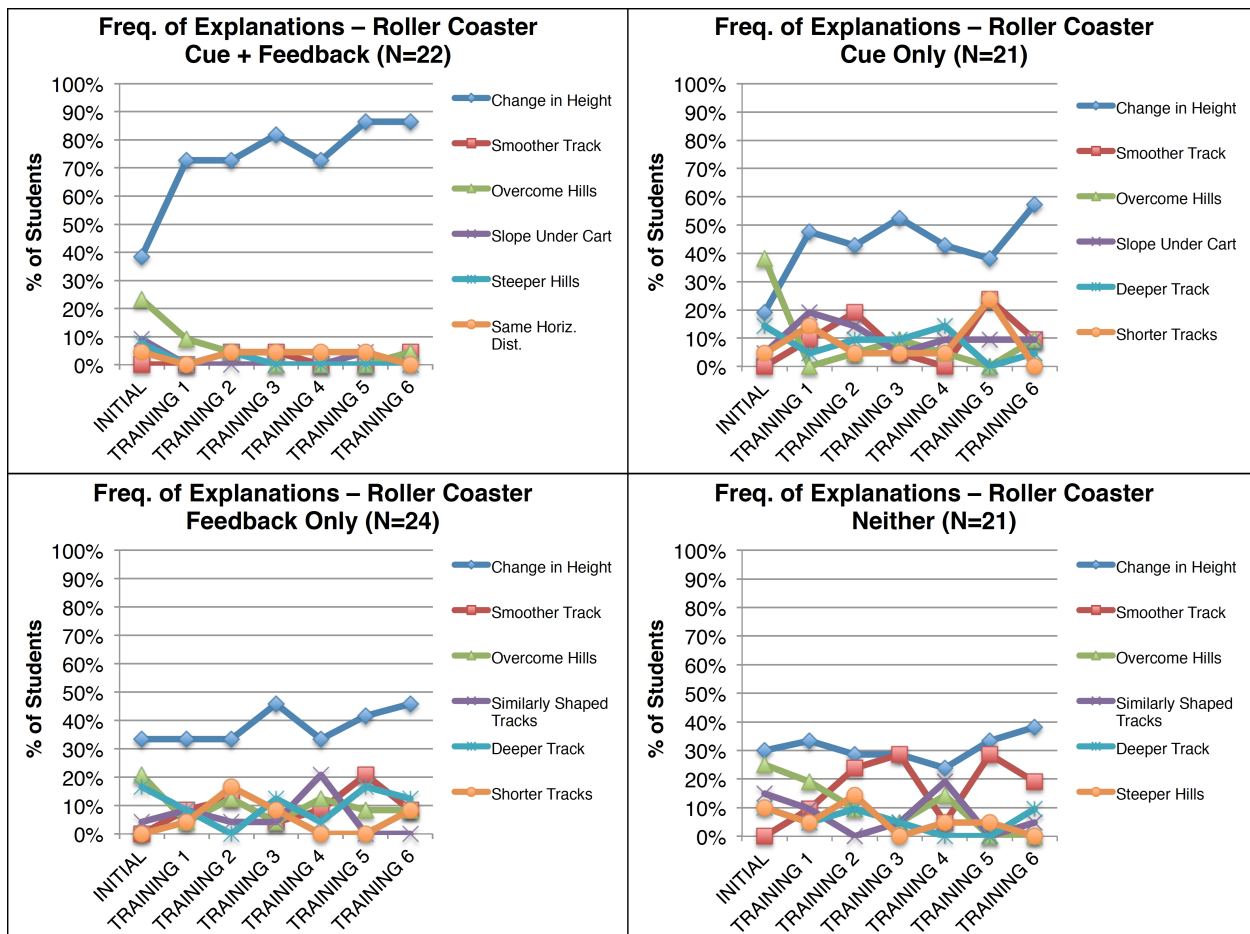
Again, we observed that students in the Cue Only and Feedback Only conditions exhibited a larger number of unique reasoning patterns while working through the problem sets than those in the Cue + Feedback group. By the second training problem, nearly 80% of students in the Cue + Feedback group were able to provide a correct solution. The most common responses provided by students in each condition are summarized in Table 4.4 and Figure 4.7 shows how student responses evolved over time.

Table 4.4 Summary of the most common explanations provided by students while solving the Roller Coaster problem. The inter-rater reliability was 93%.

Resource	Explanation	Frequency
Change in Height	Change in height = change in kinetic energy/speed	46.4%
Smoother Track	Smoother tracks with fewer/smaller hills will have faster carts	9.1%
Overcome Hills	Deeper dips in the track are harder to overcome and slow down the cart	8.8%
Deeper Track	Deeper dips in the track will increase the speed of the cart	6.0%
Shorter Track	Shorter tracks (in terms of physical distance traveled) = faster carts	4.9%
Slope Under Cart	Steeper slope at final position = faster cart	4.2%
Similarly Shaped Tracks	Tracks with similar shapes will have the same final speed	3.7%
Steeper Hills	Steeper hills will increase the speed of the cart	1.86%
Same Horiz. Distance	Same horizontal distance traveled = same final speed	0.9%

The most common incorrect responses provided by students related to the shape of the track. These responses included tracks with smaller bumps have less to overcome, and therefore would produce a faster cart. Interestingly, the Slope Under Cart resource was only activated by students in the two cued conditions, though it was a relatively uncommon explanation (accounting for just 4.2% of all responses). One possible explanation is that some students in the cued conditions may have noticed the slope of the track beneath the carts only after the carts were highlighted during the cue.

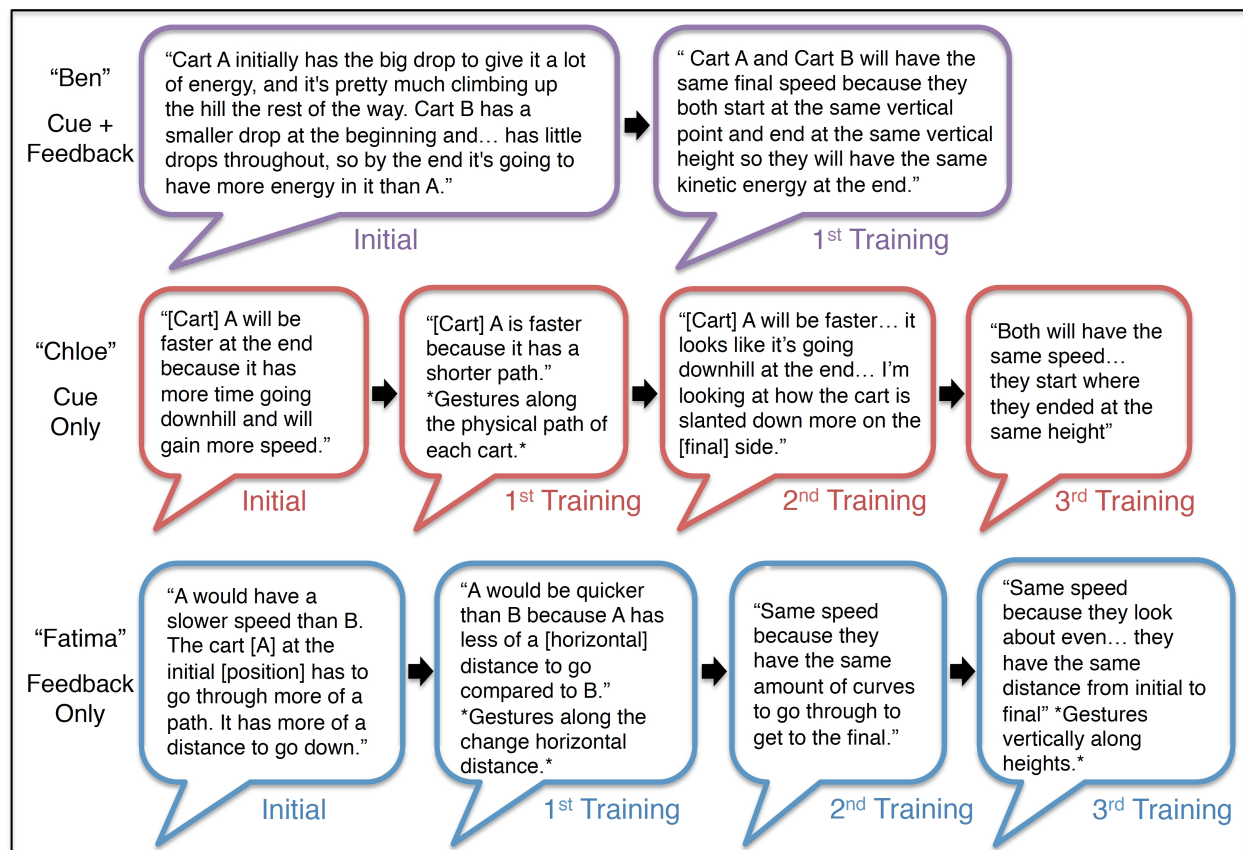
Figure 4.7 Evolution of student responses to the Roller Coaster over time. The six most common responses provided by students in each condition are shown in each of the graphs below.



Examples of Student Responses

To better understand how students' activation of resources changed as they progressed through the problem set, we present transcribed responses for three students – Ben, Chloe, and Fatima who were in the Cue + Feedback, Cue Only, and Feedback Only conditions, respectively. All three students provided incorrect responses to the initial problem, providing a track-dependent explanation. However, all three students eventually successful in switching to a correct response. The evolution of their responses as they switched from an incorrect to correct responses is summarized in Figure 4.8.

Figure 4.8 Evolution of student responses on the Roller Coaster problem from incorrect to correct



Similar to Beth, Ben was able to provide a correct solution to the first training problem, after learning that his response to the initial problem was incorrect and being provided with a cue on the first training problem. Ben initially explained that the cart on the track with smaller hills

would have more energy at the final position and would therefore have a greater speed. Once he saw the cue on the first training problem, Ben explained that the carts would have the same final speed because their initial and final positions were the same, and would therefore have the same amount of kinetic energy.

Several students in the Cue Only condition would often try incorporate the cue into their response. Chloe could have been using the cue to justify her track-based explanations to the first two training problems. The side to side motion of the cue may have lead her to think of the horizontal distance traveled by the carts and therefore cite it as her explanation to the first training. Likewise, on the second training problem, Chloe may have noticed the shape of the track directly beneath the cart while the starting and final positions of the cart were highlighted leading her to cite the slope of the track underneath the cart at its final position while justifying her response. By the third training problem onward, Chloe was able to successfully interpret the cue and compared the starting and ending heights of the carts when to compare their final speeds.

Fatima, like many others in the Feedback Only condition, provided several different responses until citing track-based features including the depth of the hills, the horizontal distance traveled, and the similarity in the shapes of the tracks before arriving at a correct solution.

Discussion

In this study we investigated the effects of visual cueing and outcome feedback on students' reasoning while they solved conceptual physics problems. Two different types of cues were utilized in this research – enhancement and elaboration cues. Enhancement cues aid problem solvers in the selection of the critical information in the diagram by emphasizing relevant features and/or suppressing irrelevant features which then ultimately leads to successful re-encoding. Elaboration cues help the problem solver enrich the representation by facilitating the appropriate comparisons within the diagram. A learner attending to the information provided by these cues may activate previously dormant conceptual resources from long-term memory and eventually allowing them to successfully re-represent the problem.

We found that the combination of visual cueing and outcome feedback is successful in helping students in correctly solving training problems they were previously unable to solve. For

both cue types, the average number of unique resources activated by students' is significantly lower than the number activated by those in the Feedback Only condition. This is likely due to the relatively short time scale it takes students to start providing correct responses. Often, students in the Cue + Feedback group are able to arrive at the correct solution within one or two training problems, whereas this process is more gradual for the Cue Only and Feedback Only groups. Upon learning that their response is incorrect and being provided with a cue on the subsequent problem, students in the Cue + Feedback condition may be more likely to abandon their previously incorrect response if the cue emphasizes features incompatible with their earlier response. For example, the cue on the Skier problem enhances the vertical distance beneath the skier, which is spatially separated from the slopes. This could contribute to the relatively sharp gains shown in Figures 4.3 and 4.6. On the other hand, students who only received outcome feedback, are unlikely to repeat a response they know to be incorrect, but without the guidance provided by the cue, it takes longer for them to find the correct response.

In both problems discussed in this chapter we find that students who see visual cues may often go through transition states in which the cue has either been accommodated into a hybrid explanation. In the Skier problem, this transition state often involves a combination of the relevant information enhanced by the cue with a previously provided response (e.g. steepness of slope + change in vertical height). In the case of the Roller Coaster problem, some students may have tried to use the cue to justify a track-based explanation (e.g. the steepness of the track beneath the cart at the final position).

Chapter 5 - Influence of Visual Cueing on Eye Movements: Visual Cues Facilitate Automaticity in Extracting Relevant Information¹

Introduction

This chapter investigates the relationship between lower-level visual attention processes and higher-level physics problem solving. This is challenging, because most of what we know about attention has to do with its lower-level perceptual processes, and most of what we know about problem solving has to do with much higher-level cognitive processes. Thus, forging a link between lower-level perception and higher-level cognition is difficult. A vast literature has developed over the past 40 years explaining the low-level stimulus factors that capture attention and eye movements, and the effects this has on early visual perceptual processes. For example, motion has been shown to reliably capture eye movements (overt attention) (Carmi & Itti, 2006; Mital et al., 2010), as mediated by the superior colliculus in primates (Boehnke & Munoz, 2008; Findlay & Walker, 1999; Kustov & Robinson, 1996), and the optic tectum in lower animals, including toads (Borchers & Ewert, 1979). In turn, selective attention has been shown to improve perceived brightness, acuity, and contrast sensitivity (Cameron et al., 2002; Carrasco et al., 2000; Carrasco et al., 2002), as mediated by an increased signal-to-noise ratio of cells as early as the primary visual cortex (Fischer & Whitney, 2009; Pestilli et al., 2011). However, despite the tremendous strides that have been made in understanding the low-level causes and effects of visual selective attention, much less is known about high-level cognitive causes and effects of visual selective attention. Admittedly, a sizeable body of research has shown strong relationships between tasks and selective attention, as measured by eye movements (Einhauser et al., 2008; Foulsham & Underwood, 2007; Henderson et al., 2007), and between selective attention, as measured by eye movements, and memory (Hollingworth & Henderson, 2002;

¹ The work in this chapter has been published previously as:

Rouinfar, A., Agra, E., Larson, A. M., Rebello, N. S., and Loschky, L. C. (2014). Linking attentional processes and conceptual problem solving: visual cues facilitate the automaticity of extracting relevant information from diagrams. *Frontiers in Psychology*, 5, 1094. doi: [10.3389/fpsyg.2014.01094](https://doi.org/10.3389/fpsyg.2014.01094) (included under the terms of the Creative Commons Attribution License 4.0)

Pertsov et al., 2009; Zelinsky & Loschky, 2005). Nevertheless, far less research has investigated such causal relationships between visual selective attention and eye movements on the one hand, and quintessentially higher-level cognitive processes such as those involved in problem solving, on the other.

In this chapter, we specifically investigate the relationships between visual selective attention and the cognitive processes involved in solving physics problems, which are among the most intellectually and cognitively demanding that human beings are capable of engaging in. Indeed, one might reasonably ask whether such low-level perceptual functions as those involved in selective attention could really play much of a role in such a high-level cognitive task. However, several studies over the last decade have shown exactly that, namely that cueing people's attention in specific ways while they solve insight problems can significantly affect their solution accuracy (Grant & Spivey, 2003; Thomas & Lleras, 2007, 2009). In the current study, we have investigated these processes in the context of learning from problem solving. However, evidence of learning, as shown by increased performance on problem solving tasks alone, while clearly implicating memory formation, cannot elucidate the links between online attentional selection and the higher-level cognitive processes involved in physics problem solving. We therefore elucidated the online processes that link attention selection and physics problem solving by using eye movement data in conjunction with increases in problem solving performance.

Motivation

Our research was inspired by the groundbreaking work of Thomas and Lleras (2007, 2009), which demonstrated that shifting overt or covert attention in ways that embody the solution to Duncker's (1945) tumor problem improved performance on it, even without solvers being aware of the relevance of the cueing to finding the problem's solution. The concept of having attentional movement trajectories embody the solution to a problem, while powerful, may not apply to solving a wide array of problems. However, the simpler relationship between what is selected for visual attention and how that affects problem solving cognitive processes can be investigated in most if not all problems involving figures.

Our particular approach to investigating this issue has been to use specific physics problems that contain two distinct regions, those associated with well-documented misconceptions and those associated with correctly solving the problems. In this way, a direct connection can potentially be found between overt attentional selection and problem solving cognitive processes. The results of these studies showed that when attempting to solve such problems, solvers' overt attention was strongly guided by mandatory top-down processes (prior knowledge, either correct or mistaken) to either the relevant or irrelevant regions respectively (Madsen et al., 2012; 2013a). Our prior work has shown that higher-level cognitive processes involved in physics problem solving very strongly guide solvers' overt attentional selection. Furthermore, overt attentional selection of relevant (rather than irrelevant) information is associated with a higher probability of correctly solving such problems. However, we have also shown that simply guiding solvers' overt attention to relevant areas of physics problems is often insufficient to correctly solve those problems, or transfer problems similar to them.

The Current Study

Our prior results described above left important open research questions. Specifically, although previous work clearly showed that higher cognitive processes strongly affect attentional selection during insight problem solving, much less clear is the degree to which attentional selection, as guided by visual cues, can strongly affect higher-level cognitive processes involved in conceptual physics problem solving.

We therefore considered our previous results in terms of their relationship to Ohlsson's (1992) model of insight problem solving, which suggested that we make several changes to our methodology. These changes were done in order to facilitate both the guidance of overt attention to relevant information, and the use of that information to restructure solvers' representations of the problems and find correct solution paths. Specifically, although several previous studies had shown that the solvers' success rate in solving Dunker's radiation problem could be increased by their cueing attention without explaining why (Grant & Spivey, 2003; Thomas & Lleras, 2007; 2009), we repeatedly found that simply guiding solvers' attention to the relevant information in a problem was insufficient for them to arrive at a correct solution path (Madsen et al., 2012;

2013a). Thus, we decided to explicitly indicate to solvers that the cues were relevant to solving the problems, by referring to the cues as “hints,” which were meant to help them.

In addition, we previously observed that solvers who were incorrect on the first problem in a set of similar problems tended to repeatedly use the same incorrect solution path for every problem in the set. Thus, in terms of Ohlsson’s model of insight problem solving (1992), the solvers were apparently not facing an impasse that would force them to restructure their faulty representation of the problem. This points out a difference between our problems and many common insight problems, for example Maier’s Two-String Problem (Maier, 1931). In our problems the solver may not know that they have failed to reach the goal state, whereas many insight problems are structured such that failure to reach the correct goal state is self-apparent. We therefore decided to provide the solvers with correctness feedback (i.e., saying “correct” or “incorrect” without explaining why) after they gave their answer to each problem. This would facilitate their entering an impasse for those problems they solved incorrectly, with the idea that solvers could then potentially break their impasse by restructuring their representations of those problems. In such cases, the visual cues could direct solvers’ attention to relevant information, which could activate previously dormant relevant knowledge from long-term memory, enabling the solver to create a new representation for the problem that could break the impasse. In order to determine the individual effects of correctness feedback and visual cueing on overt attention and problem solving, we manipulated both factors independently in our experimental design.

We also incorporated a key idea from de Koning and colleagues’ (2009) model of attentional cueing for learning, specifically that cues can be used not only to facilitate selecting important information for attention, but also to facilitate integrating information across different regions within a problem. For instance, cues can facilitate making comparisons between different elements of a problem, such as comparing the distance traveled at different points in time, or comparing the slopes of two curves on a graph. Such cues still function to direct the solvers’ attention, but go beyond simply directing attention to a location in space by symbolically indicating the types of information to attend to at those locations, and between different locations over time.

In order to measure changes in attentional selection and problem solving over time (i.e., learning), as in our previous studies (Madsen et al., 2012; 2013a), for each base problem, we created a series of similar problems, which will be discussed in the Methods section. Furthermore, as in our previous studies (Madsen et al., 2012; 2013a), in order to test for more than just superficial learning, we created transfer problems that used the same underlying reasoning (and solution paths), but had somewhat different surface features. In addition, we did not use cues on either the initial problem for each sequence, or on the transfer problem for that sequence, in order to measure both overt attentional selection and problem solving cognitive processes in the absence of cueing.

Given the above discussion, it is worth considering what changes in perceptual and higher level cognitive processing might occur as a consequence of learning engendered by cueing problem solvers on successive trials, each with a similar problem that differs only minimally in its surface features from the previous problem, and then testing on a transfer problem that differs more substantially in its surface features. Changes in solvers' problem representations could be measured off-line in terms of giving correct answers on the transfer problems by solvers who had given incorrect answers on the initial problem for that problem type. Of particular interest for the current study, we can also measure such changes in the solvers' problem representations on-line in terms of eye movement data, for example by solvers overtly attending to relevant information on transfer problems that they had previously ignored in the initial problem of that problem type. A more specific hypothesis is that solvers who had previously been cued would have learned to attend to the relevant information, and thus spend more time processing the relevant information on the transfer problem than those solvers who had not been previously cued. We will call this the processing priority hypothesis. Interestingly, however, an alternative competing hypothesis is suggested by considering a further aspect of learning, namely automatization (Schneider & Shiffrin, 1977), which could be measured in terms of increased efficiency of information extraction and integration into a solution path in WM. Assumedly, repeatedly attending to relevant information and using it to create a similar correct solution path would engender greater automaticity (i.e., efficiency) in performing each of these perceptual and cognitive processes. Automatization as shown by eye movements could be measured in terms of fixation durations, which are generally taken as an indication of processing difficulty (Nuthmann et al., 2010; Rayner, 1998). Thus, to the degree that relevant information

extraction and integration is automatized, it should produce shorter fixation durations. More specifically, an alternative hypothesis is that solvers who had previously been repeatedly cued should process the relevant information in a more automatized manner, and thus have shorter fixation durations on the relevant information on the transfer problem than those solvers who had not been previously cued. We will call this the automatization hypothesis.

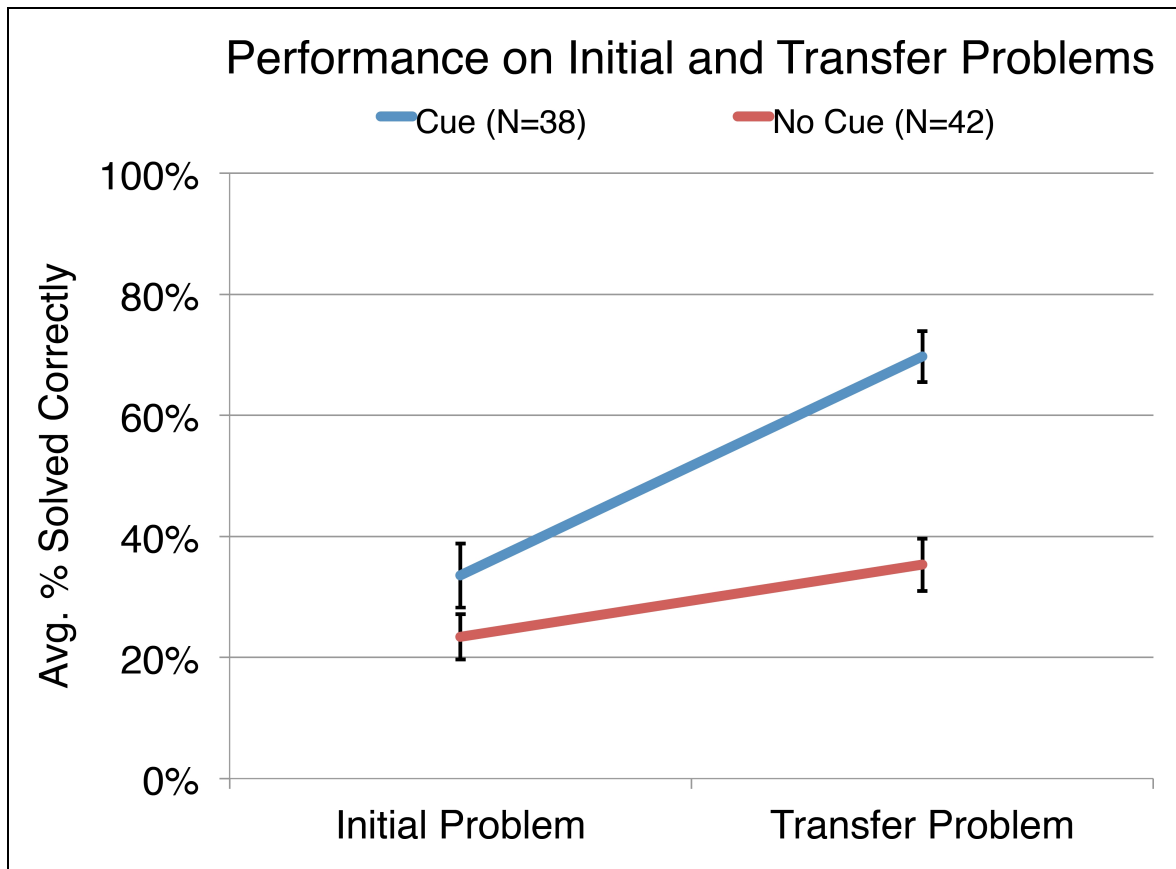
Analysis and Results

Ten participants had unusable eye movement data files and were eliminated from further analysis in this chapter. Of the remaining 80 participants, 38 were in a cued condition (22 males, 16 females) and 42 were in an uncued condition (22 males, 20 females). In the initial analyses of the data presented in this chapter, we found no significant main effects of feedback, nor any interactions of feedback with cueing, on any eye movement measures. Therefore, to streamline our description of our results, we have collapsed across the feedback factor and will not discuss that factor further.

Correctness

We were first interested in the pedagogical effectiveness of the visual cues in helping participants correctly solve and reason about the problems. Figure 5.1 shows the average percentage of initial and transfer problems solved correctly (correct in terms of both the answer and explanation) by the participants in the cued and uncued conditions. On average, participants in the uncued condition correctly solved 23.4% of initial problems and 35.3% of transfer problems. Participants in the cued condition correctly solved an average of 33.6% of initial problems and 69.7% of transfer problems. To compare the performance of the cued and uncued participants, a repeated measures ANOVA was conducted with the proportion of the initial and transfer problems correctly solved as the within-subjects factor and the condition as the between-subjects factor.

Figure 5.1 The average percentage of initial and transfer problems answered correctly by participants in the cued and uncued conditions. The error bars indicate ± 1 standard error of the mean.



The results of the ANOVA indicated that there was a main effect of problem, $F(1, 78)=64.55, p<.001$ and of condition, $F(1, 78)=16.45, p<.001$. These main effects were qualified by a significant interaction, $F(1, 78)=16.45, p<.001$ indicating that participants in the cued and uncued conditions performed differently depending on the problem. Probing the interaction we find that there was no significant difference in the average proportion of initial problems answered correctly by participants in the cued and uncued conditions, $F(1, 78)=3.42, p=.068$. However, those in the cued condition, on average, correctly solved a significantly larger proportion of transfer problems than those in the uncued condition, $F(1,78)=39.38, p<.001, d=1.07$. Both those in the cued and uncued conditions showed a significant increase from initial to transfer, $F(1, 78)=69.11, p<.001, d=1.23$ and $F(1, 78)=8.28, p=.005, d=.45$, respectively. After watching cues on the training problems, participants in the cued condition solved nearly twice the proportion of transfer problems correctly as compared to participants in the uncued

condition. These results demonstrate that the visual cues significantly improve performance on the transfer problem. More importantly, the results suggest that the visual cues promote higher level cognition as evinced by the improved performance on the transfer problem.

Comparing the Attention of Correct and Incorrect Solvers on the Initial Problem

Madsen et al. (2012) showed that correct and incorrect solvers differ in their allocation of visual attention while solving problems with diagrammatic features consistent with novice-like answers in addition to thematically relevant regions. Specifically, participants who answer the problems correctly spend significantly more time attending to the thematically relevant areas and a significantly smaller proportion of time attending to the features associated with the novice-like answers than participants who answer the problems incorrectly. The novice-like and thematically relevant areas in the problems investigated in this study are depicted in Figure 5.2. We performed a similar analysis to determine if the correctness on the initial problem could be attributed to participants' attention in the thematically relevant and novice-like regions.

To analyze the eye movements, areas of interest (AOI) were drawn around the thematically relevant and novice-like areas associated with each problem with a border of 1.1° of visual angle. (One degree of visual angle is approximately the size of one's index fingernail when held at arm's length.) The size of the areas was determined by using an error propagation technique (Preston and Dietz, 1991) which took into account both the eye tracker's accuracy and the spatial extent of the central fovea (0.5° and 1° of visual angle, respectively). When comparing eye movements across several problems, the physical sizes of the thematically relevant and novice-like areas are non-constant and should be normalized. To do this, we divided the percentage of dwell time in the AOI by the percentage of screen that the AOI subtends. This produced a new measure, the percentage of total dwell time divided by the percentage of total area, which is described as the domain relative ratio (Fletcher-Watson et al., 2008).

Figure 5.2 An example of the thematically relevant area and novice-like area in an initial problem. Respectively, these areas are associated with the correct response (time interval when the balls travel the same distance) and most common incorrect response (time when the balls are at the same position).

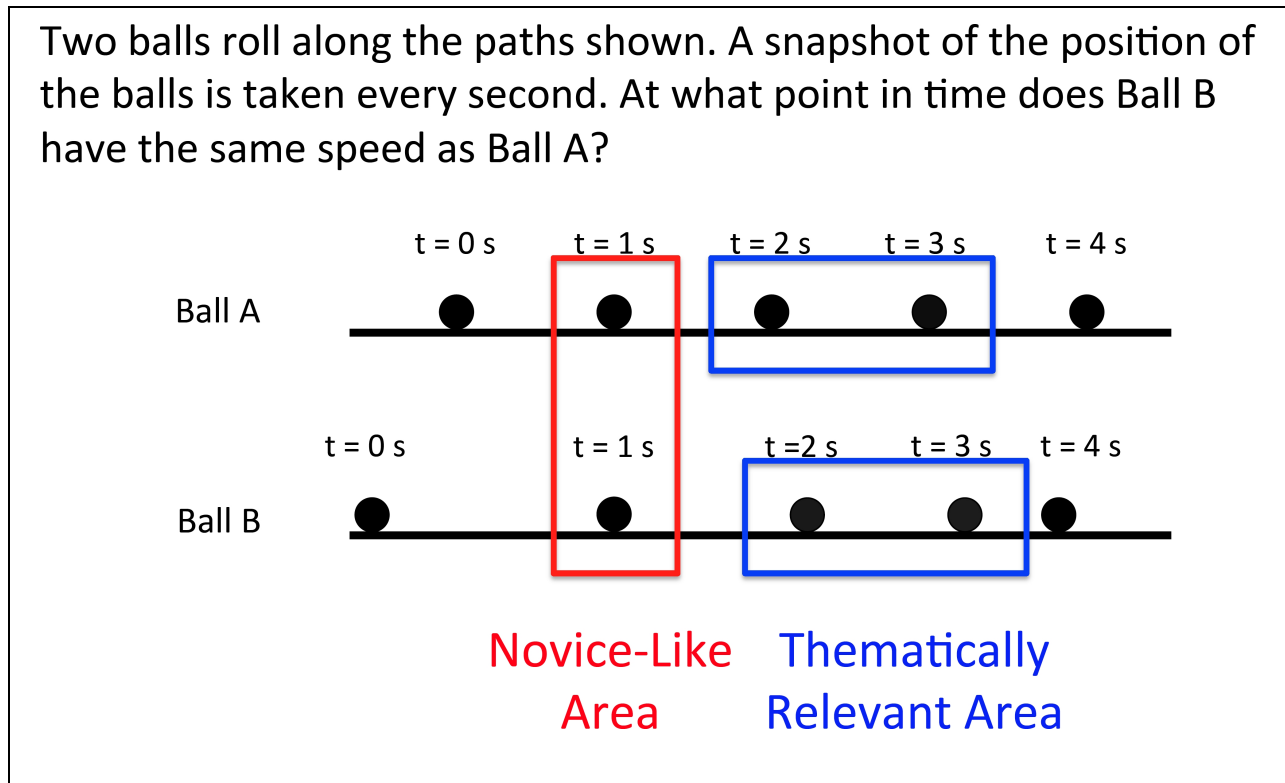
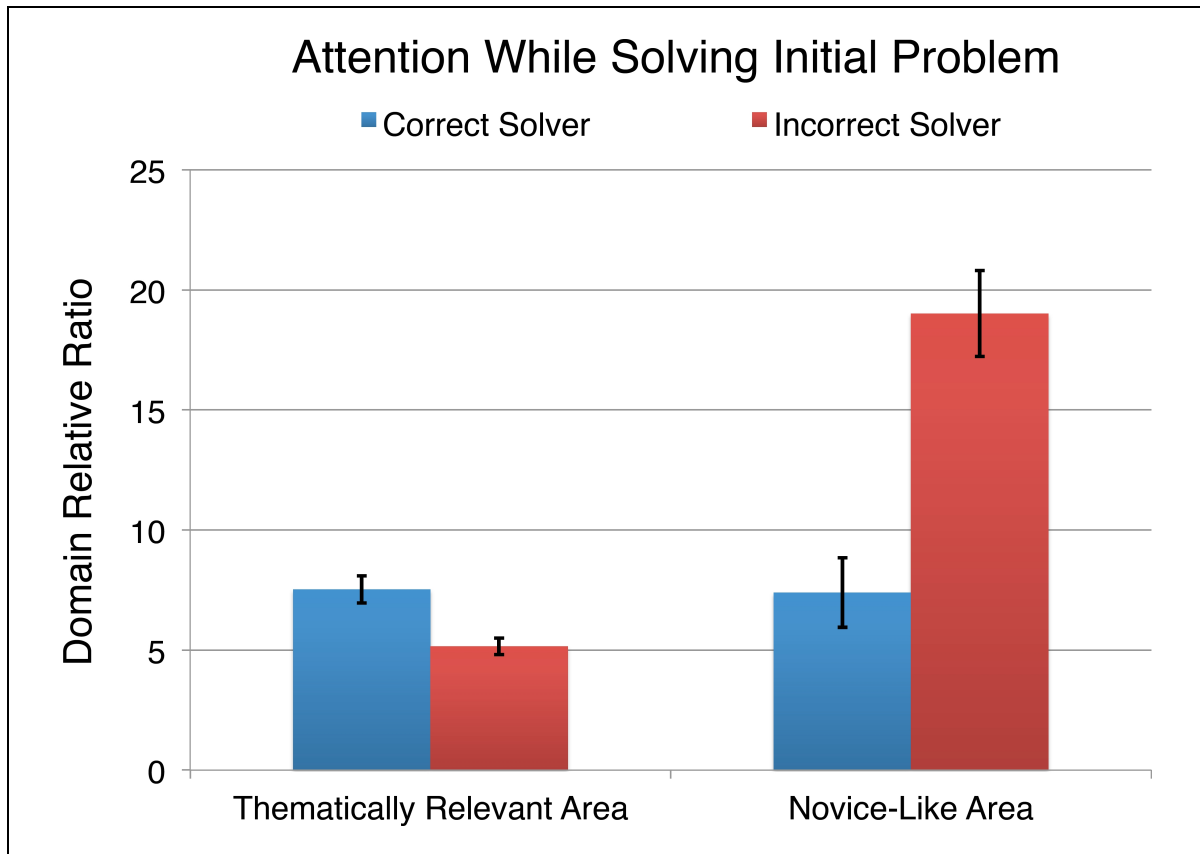


Figure 5.3 shows the domain relative ratio spent by correct and incorrect solvers in the thematically relevant and novice-like areas while they solved the initial problem in each set. To compare the proportion of time that correct and incorrect solvers spent attending to the thematically relevant and novice-like areas, we conducted two one-way ANOVAs with the domain relative ratio as the dependent measure and correctness as the between-subjects factor. The results indicate that those who solved the initial problem correctly had a significantly larger domain relative ratio in the thematically relevant area, $F(1, 318)=13.20, p<.001, d=.44$ while simultaneously spending a significantly smaller domain relative ratio in the novice-like area, $F(1, 318)=14.85, p<.001, d=.47$. These results are consistent with Madsen et al.'s (2012) findings.

Figure 5.3 The domain relative ratio (percentage of dwell time divided by the percentage of area the AOI encompasses) in the thematically relevant and novice-like areas on the initial problem by the correctness of response. Error bars indicate ± 1 standard error of the mean.



Attention While the Cue Played

Participants in the cued condition were required to play the cues on the training problems at least once, but were allowed to replay the cue as many times as desired. The vast majority of the time the participants chose to play the cues just once, accounting for 90.4% of all training problems solved. The cue was played twice 8.1% of the time, 55.4% of which occurred during the first training problem in a set.

We investigated whether participants who most needed to see the cue (namely those who provided an incorrect response to the immediately preceding problem in the set) actually watched the cue while it was on screen. We found that those who switched to a correct response had, on average, a domain relative ratio of 16.5 spent watching the cue while it was on screen, while those who retained an incorrect response had a domain relative ratio of 13.2. To compare

these values, a one-way ANOVA was conducted with the domain relative ratio as the dependent measure and correctness pattern as the between-subjects factor. The results indicated that the cued participants who switched to a correct response spent a significantly larger proportion of time per area watching the cue, $F(1, 277)=7.71$, $p=.006$, $d=.34$. This result demonstrates that watching the cue more closely can be tied to participants switching from an incorrect to correct response.

Changes in Eye Movements among Participants who Demonstrated Learning

Thus far, we have demonstrated that cues can be an effective learning tool and that there is a link between the correctness of a student’s response and their allocation of attention while solving the problem. We now consider the subset of participants who we can reasonably assume learned something—that is, those who answered the initial problem incorrectly, but after working through the training problems were successful in correctly solving the transfer problem. Each case in which a participant demonstrated learning was treated as an independent observation in the analyses described later in this section. Across all problem sets, we have 66 cases (34 unique participants) of this occurring in the cued group and 30 cases (21 unique participants) in the uncued group, corresponding to 89.5% and 50.0% of participants in the cued and uncued groups, respectively. There was significantly greater number of participants in the cued condition following this pattern than in the uncued condition, $\chi^2(1, N = 320) = 24.83$, $p < .001$, $V = .279$. The number of participants demonstrating learning on one or more problems is provided in Table 5.1.

Table 5.1 The number of problem sets in which participants demonstrated learning in the cued and uncued conditions.

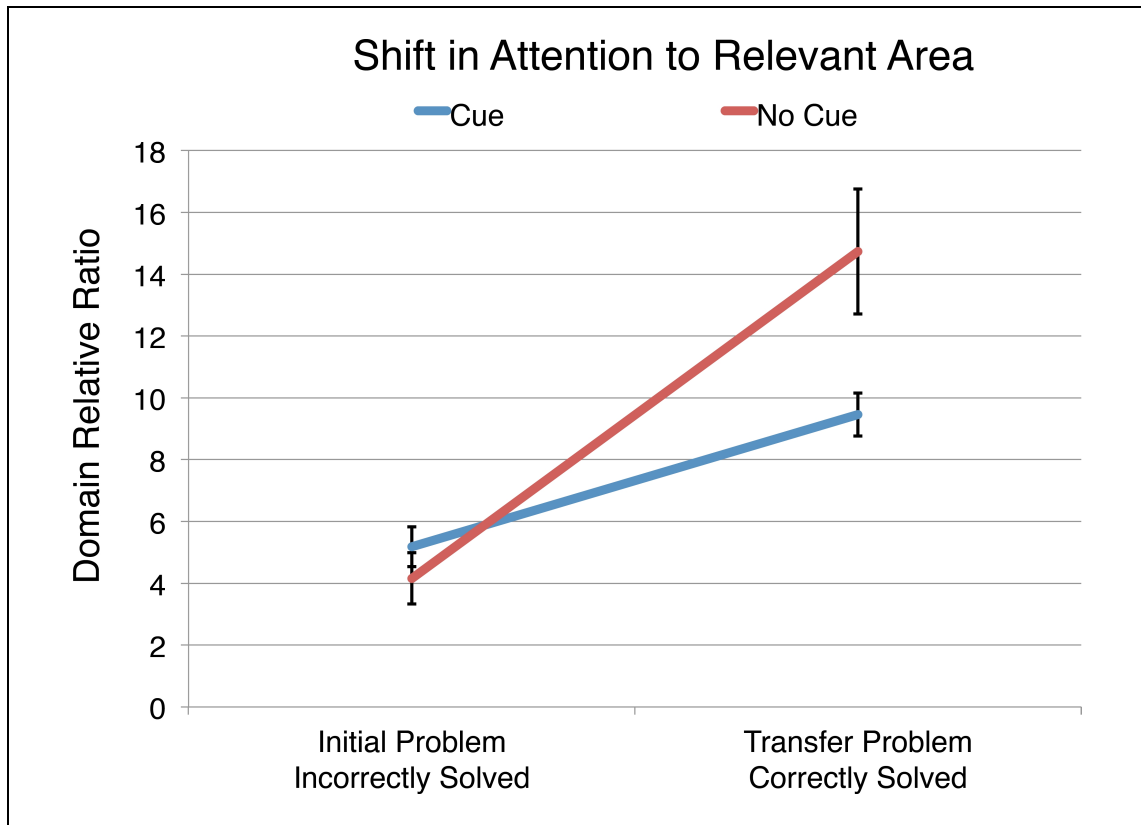
Condition	Number of Participants Demonstrating Learning on:			
	1 Problem Set	2 Problem Sets	3 Problem Sets	4 Problem Sets
Cue (N=38)	11	16	5	2
No Cue (N=42)	13	7	1	0

As indicated by Table 5.1, the analyses reported below contained cases in which some participants contributed only a single observation, whereas other participants contributed multiple observations, across all problem sets. Thus, we did not include “problem set” as a within-subjects factor in our analyses due to missing data. Because having different numbers of observations across problem sets as a function of participants could create additional within-subject dependencies in our analyses, we carried out a robustness check. Specifically, we carried out the analyses discussed in this section on a randomly selected subsample of the data in which no participant contributed more than a single observation. The results of these additional analyses showed the same pattern of results reported below—all significant main effects and interactions reported below were also significant with only the randomly chosen subsample (see Appendix B for these additional analyses). Therefore, for all analyses reported in this section, we have included the full data set shown in Table 5.1.

Attention in the Thematically Relevant Area

After finding that correct solvers spent a significantly larger proportion of their time attending to the relevant area, we wanted to see if the participants who demonstrated learning had an increased domain relative ratio in the transfer problem. Figure 5.4 shows the domain relative ratio that cued and uncued participants spent in the relevant area on the initial and transfer problems.

Figure 5.4 The domain relative ratio (percentage of dwell time divided by the percentage of area the AOI encompasses) in the thematically relevant area on the initial and transfer problems for those who improved from the initial to transfer problem. The error bars indicate ± 1 std. error of the mean.



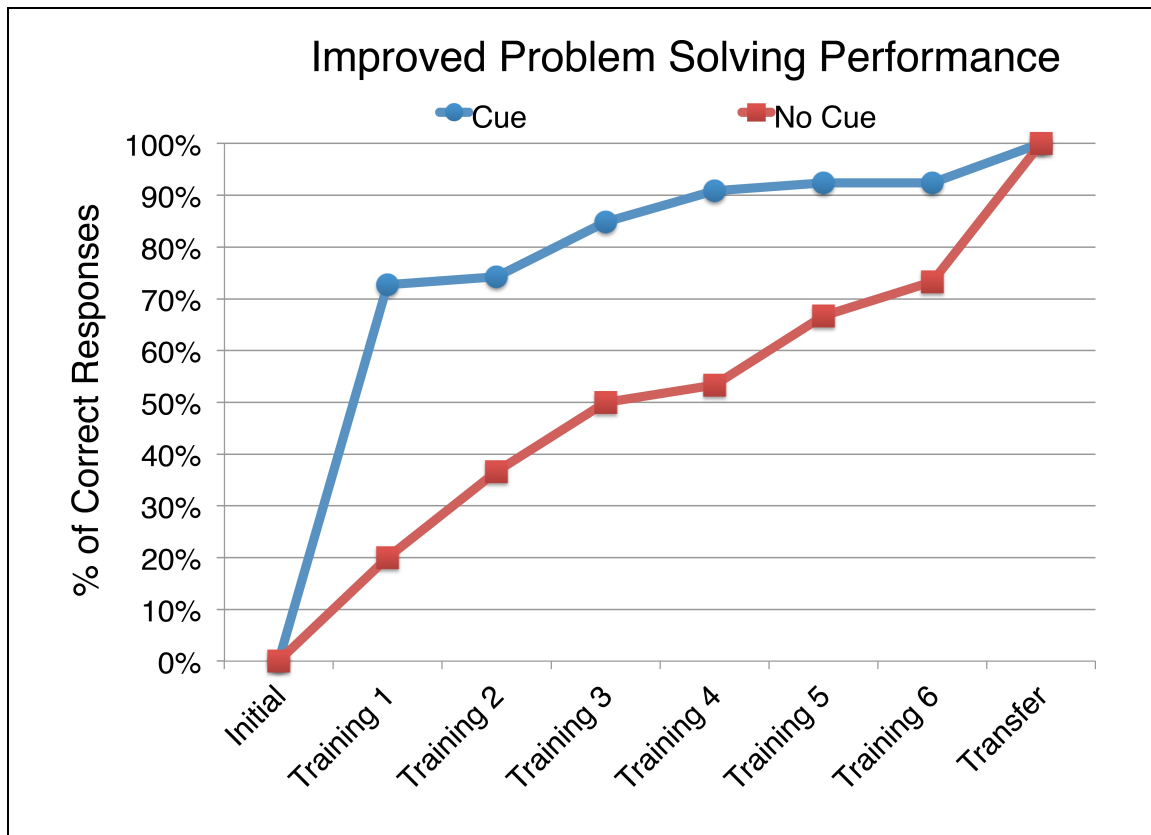
A repeated measures ANOVA with domain relative ratio in the thematically relevant area as the dependent measure and condition as the between-subjects factor was conducted. There was a significant increase in the domain relative ratio in the relevant area from the initial to the transfer problem, $F(1, 94)=56.41, p<.001$ and a significant main effect of condition, $F(1, 94)=4.12, p=.045$. However, these main effects are qualified by a significant interaction, $F(1, 94)=10.17, p=.002$, indicating that the cued and uncued groups performed differently depending on the problem. Probing the interaction we find that both the cued and uncued groups increased significantly from initial to transfer problem, $F(1, 94)=14.94, p<.001, d=.79$ and $F(1,94)=41.63, p<.001, d=1.35$, respectively. However, while there was no significant difference between the cued and uncued conditions on the initial problem, $F(1,94)<1$, the uncued condition had a significantly higher domain relative ratio in the relevant area than the cued condition on the transfer problem, $F(1, 94)=14.25, p<.001, d=.65$.

Inconsistent with the processing prioritization hypothesis, among participants who showed evidence of learning (i.e. improved performance on the transfer problem relative to the initial problem), those who saw cues spent significantly less time attending to the relevant area on the transfer problem than those who did not see cues. This is despite the fact that solvers in the cued condition received training to attend the relevant area. This result is surprising, and seems to pose a paradox. Namely, why would those trained to attend to the relevant area spend less time attending to the relevant area than those who were not trained to do so? A possible solution of this paradox is given by the automatization hypothesis, namely that those who were given training with the cues may have developed greater automaticity in extracting the relevant information, and thus spent proportionally less time attending to the relevant area of the transfer problem than those solvers who did not receive the cued training (i.e., the uncued participants).

Automaticity in Extracting Relevant Information

We hypothesized that the reason the cued group had a smaller domain relative ratio in the thematically relevant area on the transfer problem than the uncued group was because the cued group was able to more easily extract the relevant information from the diagram, namely the automatization hypothesis. If so, evidence for the increased efficiency of relevant information extraction should be found by examining their performance on the training problems. Specifically, participants in the cued condition should have had greater success in extracting the relevant information over more trials than participants in the uncued condition, which would then produce greater automaticity of extracting relevant information for the cued group. A test of this hypothesis is shown in Figure 5.5, which shows student performance across all problems within the sets.

Figure 5.5 The performance on each problem for the subset of participants who shifted from an incorrect response on the initial problem to a correct response on the transfer problem.



Consistent with the automatization hypothesis, among cued participants who answered the initial problem incorrectly, we find that 73% were able to correctly solve the first training problem, and the proportion increased to 92% by the sixth training problem. In contrast, only 20% of the uncued group answered the first training problem correctly, and by the sixth problem 73% were correct. Because a larger proportion of participants in the cued group were able to answer the training problems correctly, they had more practice doing so, and thus gained more automaticity in extracting the relevant information. In addition, the increase in percentage of correct responses in the two groups from the sixth training problem to the transfer problem was greater for the uncued group — that is, getting the transfer problem correct was a bigger leap for more of those in the uncued condition than those in the cued condition.

To statistically compare the cued and uncued participants' performance depicted in Figure 5.5, a survival analysis was conducted. To do this, the training problem number in which the participant switched to providing only correct responses was considered. Comparing the resulting survival curves using a log-rank test indicates that the participants who saw cues on the training problems switched to a correct response significantly earlier than those in the uncued group. $\chi^2(1, N = 96) = 16.17, p < .001$. Altogether, these conditions likely led to the cued group having greater ease of extracting the relevant information (indicated by the smaller domain relative ratio) on the transfer problem than the uncued group (as shown in Figure 5.4).

Average Fixation Duration in the Thematically Relevant Area

A further test of the automatization hypothesis is in terms of the successful problem solvers' average fixation durations. We would expect that increased ease of extracting the relevant information, namely greater automaticity, would be associated with shorter fixation durations in the relevant area. Table 5.2 shows the average fixation durations of the cued and uncued participants in the relevant area and entire diagram for the transfer problems. (Note that there was no cueing on the transfer problem, even in the Cued condition.)

Table 5.2 The average fixation durations (in ms) \pm 1 standard error of the mean for the cued and uncued groups in the relevant area and entire diagram while viewing the transfer problems.

Area of Interest	Avg. Fixation Duration in ms (Mean \pm Std. Error)	
	Cued (N=66)	Uncued (N=30)
Relevant Area	239 \pm 10	280 \pm 15
Entire Diagram	227 \pm 6	219 \pm 7

The average fixation durations of participants while solving the transfer problems were compared using a 2 (cue vs. no cue) x 2 (entire diagram vs. relevant area) ANOVA. The results are summarized in Table 5.3.

Table 5.3 Results of a 2 (cue vs. no cue) x 2 (entire diagram vs. relevant area) ANOVA comparing the average fixation duration on the transfer problem.

Effect	<i>F</i>(1, 94)	<i>p</i>	<i>d</i>
Main Effect of Area (Entire Diagram vs. Relevant Area)	23.33	<.001	.42
Main Effect of Condition (Cued vs. Uncued)	1.72	.193	–
Interaction of Area*Condition	10.87	.001	–
Simple Effect of Area (Cue Only)	1.88	.174	–
Simple Effect of Area (Uncued Only)	24.01	<.001	.96
Simple Effect of Condition (Entire Diagram Only)	<1	n.s.	–
Simple Effect of Condition (Relevant Area Only)	10.90	.001	.64

A significant interaction between the condition and area of interest was found. Probing the significant interaction, we find that within the relevant area, cued participants had significantly shorter mean fixation durations than those in the uncued condition. This is consistent with the hypothesis that the cued participants had indeed developed greater automaticity in extracting information from the relevant area than the uncued participants. We also found that uncued participants had significantly larger fixation durations in the relevant area of the diagram compared to their average fixation durations when considering the entire diagram. However, for those in the cued group, the average fixation duration in the relevant area is not distinguishable from the rest of the problem. The combination of these results indicates that cued participants experience a greater ease of extraction of the relevant information on the transfer problem, as evidenced by their lower fixation durations. This would explain why the cued group spends a smaller proportion of time attending to the relevant area on the transfer problem (as shown in Figure 5.4).

Discussion

In this study we investigated the relationship between the low-level perceptual processes involved in overt attentional selection by visual cues, on the one hand, and the high-level

cognitive processes involved in solving physics problems. Eye movements can be used to elucidate what information within a diagram is being processed and when that information is being processed. This allows for us to investigate how participants' attention changes over time and relevant cognitive processes associated with problem solving. In the following sections, we revisit our hypotheses and discuss our findings.

Correctness

Based on the changes we made in the current study in comparison to our previous studies, we were able to show that visual cues did indeed improve problem solving on the transfer problems. The changes we made were those suggested by consideration of both Ohlsson's (1992) Representational Change Theory and de Koning and colleagues Framework of Attention Cueing (2009). In particular, we told solvers that the cues were meant to help them, we provided correctness feedback to induce impasses among those who originally had an incorrect solution path, and we included visual cues that facilitated not only attentional selection of relevant information, but also integration of that information across different regions of the problem. Doing so indeed facilitated solver's ability to re-represent the problem in a meaningful way allowing for the extraction of the relevant information and thus improved performance.

We found a significantly greater proportion of participants who received training with visual cues were able to subsequently correctly solve the transfer problem without cues than those who received training in the uncued condition. We observed that both the cued and uncued groups performed similarly on the initial problem and both experienced significant increase in performance from the initial to transfer problem. However, nearly twice as many participants in the cued condition were able to correctly solve the transfer problem as compared to participants in the uncued condition (69.7% versus 35.5%, respectively). This amounted to more than one standard deviation difference between the groups. These results provide evidence that the visual cues facilitated the participants to re-represent the problem enabling them to break an impasse and solve the problem correctly. More importantly, these results provide evidence, consistent with previous studies (Thomas & Lleras, 2009) that manipulation of low-level eye movements can influence high level cognition involved in problem solving. Nevertheless, there is a critically important difference between the results of our studies and those of Grant and Spivey (2003) and

Thomas and Lleras (2007, 2009), who proposed the provocative idea that simply having the viewer's low-level attentional movements embody a problem's solution is sufficient to facilitate finding the correct solution. Specifically, our research, including both the current and previous studies (Madsen et al. 2013a, 2013b) has shown that while attending to relevant information in a problem is a necessary condition for correctly solving the problem, it is generally not sufficient to correctly solving it. The current study has specifically shown that cues, which both draw attention to solution-relevant information, and facilitate organizing and integrating it, facilitate both immediate problem solving and generalization of that ability to new problems. In addition, the current study shows that when such cues are used across multiple problems, solvers can automatize the extraction of problem-relevant information extraction.

Changes in Eye Movements

In the current study, we were particularly interested in the online processes linking overt attentional selection with higher-level cognitive processes involved in problem solving. Thus, we explored how participants' attention in the relevant area of the diagram changed from the initial problem to the transfer problem. For this set of analyses, we considered the subgroup of participants who demonstrated improvement in their problem solving from the initial to transfer problem. We focused on this subgroup as they were the ones who through the improvement of their responses from the initial to transfer problem, showed evidence that higher order cognitive processes were online.

We presented two competing hypotheses for how cued and uncued participants' attention in the thematically relevant area of the diagram would compare on the transfer problem. The processing priority hypothesis was that through training of attentional prioritization, solvers in the cued condition would spend a larger percentage of dwell time per percentage of area attending to the relevant features on the transfer problem, namely a higher domain relative ratio in the relevant area of the transfer problem for the cued group compared to the uncued group. Alternatively, the automatization hypothesis was that repeated training in attending to and extracting relevant information from a problem type would increase participants' efficiency in doing so, and therefore participants in the cued condition would have shorter fixation durations on the relevant features on the transfer problem than those in the uncued group.

We found that successful problem solvers attend to the relevant information in the diagram significantly more than unsuccessful solvers. When provided with cues on the training problems, participants who successfully switch to correct responses overtly attend to the cue significantly more closely. Among the subset of participants who improved their performance from the initial to transfer problem, we found that the cued group nearly doubled their percentage of dwell time per percentage of area in the thematically relevant area while those in the uncued condition more than tripled the domain relative ratio in the relevant area.

While the cued participants had a significantly larger domain relative ratio in the relevant area of the transfer problem than they did while solving the initial problem, it was still significantly less than the domain relative ratio of uncued group on the transfer problem. To investigate if this result could be tied to the cued group having developed an increased ease of extraction of the relevant information, we examined the participants' performance on the training problems as well as their average fixation durations while solving the initial and transfer problems.

In examining the training problem performance of those who improved from the initial to transfer problem, we found that the cued group showed a significant increase on the first training problem, followed by a more gradual increase on subsequent training problems. By contrast the uncued group showed a slower increase from the first training problem through the sixth training problem with nearly the same proportion of successful solvers on the sixth training problem that the cued group had on the first. This difference in the trajectories of the cued and uncued subgroups going from incorrectly solving the initial problem to correctly solving the transfer problem indicates that participants in the cued group had acquired greater practice than those in the uncued group in extracting information from the relevant area because they correctly solved a larger proportion of training problems. Therefore, the cued group would have achieved greater automaticity in extracting the relevant problem information than the uncued group. This conclusion is consistent with our finding that the cued group showed a lower mean fixation duration in the relevant area on the transfer problem compared to the uncued group.

An open question for further research is the degree to which the cueing effects in the current study were predicated on telling the solvers that the cues were helpful. Based on the

previous results of Thomas and Lleras (2007, 2009), in our previous studies we did not inform solvers that the cues would be helpful, but we found only moderate effects of visual cueing on overt attention and successful problem solving. The current study did tell solvers that the cues were “hints” meant to help them, and found strong effects of visual cueing on both overt attention and successful problem solving. Further research can experimentally vary whether solvers are told about the helpfulness of cues and see the degree to which this is important.

A further open question is the degree to which forcing the initially incorrect solvers into an impasse, either explicitly by providing them with correctness feedback, or implicitly by providing them with visual cues that focus on information they have previously ignored, is critical for creating strong effects of cueing on attentional selection and successful insight problem solving. The current study found that both cueing and correctness feedback facilitated solvers to make the transition from incorrect solution paths to correct solution paths. Interestingly, cueing by itself was more effective than feedback by itself. This raises the question of whether both created impasses. Further research will be needed to create on-line measures of impasse in both cueing and feedback conditions to determine the effects of each on entering an impasse during insight problem solving.

In summary, the current study has shown two important findings. First, short duration visual cues can improve problem solving performance on a variety of insight physics problems, including transfer problems that do not share the surface features of the training problems, but do share the underlying solution path. In other words, visual cues can facilitate solvers to re-represent a problem and overcome impasse thereby enabling them to correctly solve a problem. These cueing effects on problem solving were not predicated upon the solvers’ overt or covert attentional shifts necessarily embodying the solution to the problem. Instead, the cueing effects were predicated upon having solvers attend to and integrate relevant information in the problems into a solution path. Second, these short duration visual cues when administered repeatedly over multiple training problems resulted in participants becoming more efficient at extracting the relevant information on the transfer problem, showing that such cues can improve the automaticity with which solvers extract relevant information from a problem. These results, when combined with those of our previous studies (Madsen et al. 2013a, 2013b) suggest that low-level attentional selection processes provide a necessary gateway for relevant information to

be used in problem solving, but are generally not sufficient for correct problem solving. Instead, factors that lead a solver to an impasse (e.g., correctness feedback) and to organize and integrate problem information (e.g., organization and integration cues) also greatly facilitate arriving at correct solutions. Further research along these lines will enable us to more precisely understand the role of lower-level attentional selection in higher-level problem solving.

Chapter 6 - Conclusions

Overview of Research

The purpose of this work was to investigate the influence of visual cueing and outcome feedback on problem solving and visual attention in physics problem solving. More specifically, we investigated both students' problem solving performance and reasoning patterns as they worked through sets of conceptual physics problems. We also recorded students' eye movements while solving these problems and examined the effects that visual cueing had on their visual attention, as well as uncued transfer problems which differed in terms of context and surface features from the training problems.

Research Questions Answered

Research Question 1

In Chapter 3 we investigated the problem solving performance of students in each of the four conditions. Our first research question asked how visual cueing and outcome feedback influence the performance on the training problems (which were isomorphic to the initial problem in each set). Overall, we found that the Cue + Feedback, Cue Only, and Feedback Only groups all showed improved performance with respect to the initial problem. We found some evidence to suggest that the combination of visual cueing and outcome feedback is effective helping students provide correct responses and explanations to problems they were previously unable to solve. To be considered correct, students had to provide the correct answer and explanation.

The Cue + Feedback group was able to correctly solve the largest proportion of training problems in each of the four sets followed by the Cue Only, Feedback Only, and No Cue + No Feedback groups, respectively. Among students who provided incorrect responses to the initial problem, the performance students in the Cue + Feedback group was quite high, correctly solving upwards of 67% of training problems, on average. In the case of the Ball problem, the average percentage of training problems correctly solved by these students reached 98.7%. By contrast, students who provided incorrect responses to the initial problem in the Ball problem set,

but did received neither cues nor feedback answered an average 9.8% of training problems correctly. The results of the Chi-square test comparing the numbers of training problems solved correctly by participants in the four conditions indicate that for all problem sets the students in Cue + Feedback group were able to correctly solve the significantly highest number of training problems while the No Cue + No Feedback group had the significantly lowest performance.

Through the lens of representational change theory, these results suggest that visual cues may have helped students to re-represent the problems in a productive way through elaboration and re-encoding. The combination of visual cueing and correctness feedback produced the most successful problem solving performance among the participants in this study. Once students in the Cue + Feedback condition learn that their response is incorrect, they likely reached an impasse on the subsequent problem in the set. The visual cues could then help the student overcome the impasse and solve the problems correctly.

Research Question 2

While improved performance on the training problems is certainly a promising result, the evidence for learning would be stronger if we could demonstrate that students could subsequently solve a related problem without the aid of visual cues (namely, the transfer problem). Therefore, our second research question asked how visual cueing and outcome feedback influenced student performance on the transfer problems. Once again, we considered the subset of students who were unable to solve the initial problem in each set. We found that students who saw cues on the training problems (but not the transfer problem) and were told if their responses were correct were the highest performing group on each problem set. The Cue + Feedback group outperformed the Cue Only group by an amount ranging from 18.2% (Roller Coaster) up to 36.0% (Graph).

Research Question 3

In Chapter 4 we investigated the effects of visual cueing and outcome feedback on students' reasoning. For both elaboration and enhancement cues, we found the average number of unique resources activated by students' is significantly lower than the number activated by those in the Feedback Only condition. One possible explanation is that upon learning that their

response is incorrect and being provided with a cue on the subsequent problem, students in the Cue + Feedback condition may be more likely to abandon their previously incorrect response. On the other hand, students who only received outcome feedback, are unlikely to repeat a response they know to be incorrect, but without the guidance provided by the cue, it takes longer for them to find the correct response. We also found that students who see visual cues may often go through transition states in which they combine the relevant information enhanced by the cue with a previously provided response (e.g. steepness of slope + change in height).

Research Question 4

In Chapter 5 we investigated the relationship between the low-level perceptual processes involved in overt attentional selection by visual cues, on the one hand, and the high-level cognitive processes involved in solving physics problems. We presented two competing hypotheses for how cued and uncued participants' attention in the thematically relevant area of the diagram would compare on the transfer problem. The processing priority hypothesis was that through training of attentional prioritization, solvers in the cued condition would spend a larger percentage of dwell time per percentage of area attending to the relevant features on the transfer problem, namely a higher domain relative ratio in the relevant area of the transfer problem for the cued group compared to the uncued group. Alternatively, the automatization hypothesis was that repeated training in attending to and extracting relevant information from a problem type would increase participants' efficiency in doing so, and therefore participants in the cued condition would have shorter fixation durations on the relevant features on the transfer problem than those in the uncued group.

We found that successful problem solvers attend to the relevant information in the diagram significantly more than unsuccessful solvers. When provided with cues on the training problems, participants who successfully switch to correct responses overtly attend to the cue significantly more closely. Among the subset of participants who improved their performance from the initial to transfer problem, we found that the cued group nearly doubled their percentage of dwell time per percentage of area in the thematically relevant area while those in the uncued condition more than tripled theirs. While the cued participants had a significantly larger domain relative ratio in the relevant area of the transfer problem than they did while solving the initial

problem, it was still significantly less than the domain relative ratio of uncued group on the transfer problem.

To investigate if this result could be tied to the cued group having developed an increased ease of extraction of the relevant information, we examined the participants' performance on the training problems as well as their average fixation durations while solving the initial and transfer problems. Consistent with the automatization hypothesis we found that the cued group significantly outperformed the uncued group on the training problems, providing them with more practice in extracting the relevant information from the diagram. Additionally, we found that the cued group showed a lower mean fixation duration in the relevant area on the transfer problem compared to the uncued group indicating reduced cognitive load while processing the relevant information.

Limitations and Future Work

We find evidence to suggest that visual cueing and outcome feedback can help students correctly solve and reason about problems they were previously were unable to solve. We also find that students who are provided with cues and outcome feedback perform better on uncued transfer problems. One limitation is that these transfer problems are arguably somewhat similar to the initial and training problems and therefore could be considered more of a "near" transfer problem. To more clearly demonstrate the educational benefit of visual cueing and outcome feedback, investigation of student performance on problems which require more of a "far" transfer (i.e. problems which do not share any surface feature similarities in the text or diagram) is necessary. The time scale under which students solved the problems in this study is also quite short. In order to demonstrate long-term learning of physics concepts, it is critical for future investigations to follow up with students a few weeks after their initial participation and test their performance on the transfer problems to see what, if any, influence visual cueing and outcome feedback may have on retention.

The performance of students who receive both visual cues and outcome feedback improves very quickly. Solving six training problems may not be necessary for these students to perform well on the subsequent uncued transfer problems. Another line of future investigation could have the number training problems be adaptive to students' prior performance. This would

more closely resemble authentic computer-based learning environments. The data presented in this paper was collected in a more controlled and consequently a less naturalistic setting. Therefore, implementing visual cues and outcome feedback in an online setting would allow for students to work in a more ecologically valid environment.

It is also important to note that visual cueing does not lend itself to all possible physics problems, as the information required to obtain a solution does not always reside within the diagram. Our investigation has not covered the full scope of problems which may be amenable to visual cues, therefore future work should endeavor to expand the problem space.

In conclusion, there is much work that can be done to expand the understanding of the influence of visual cueing and outcome feedback in physics problem solving. This work suggests that the combination of visual cueing and correctness feedback can be an effective learning tool and motivates the continuation of research in this area.

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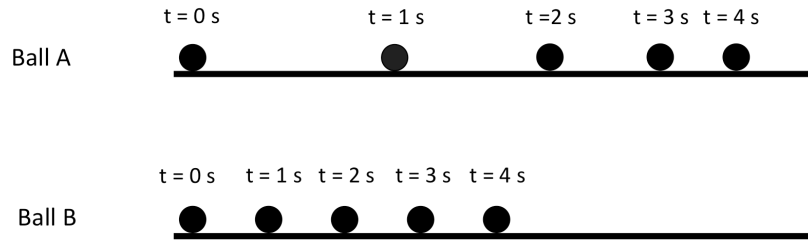
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Appendix A - Problems Investigated

Table 6.1 The Ball problem set

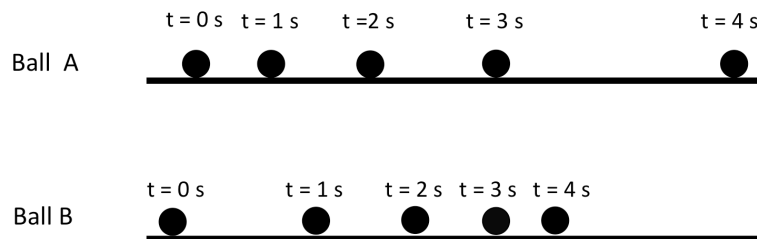
Initial Problem	<p>Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?</p> <div style="text-align: center; margin: 20px 0;"> </div>
Training Problems	<p>Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?</p> <div style="text-align: center; margin: 20px 0;"> </div>

Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?

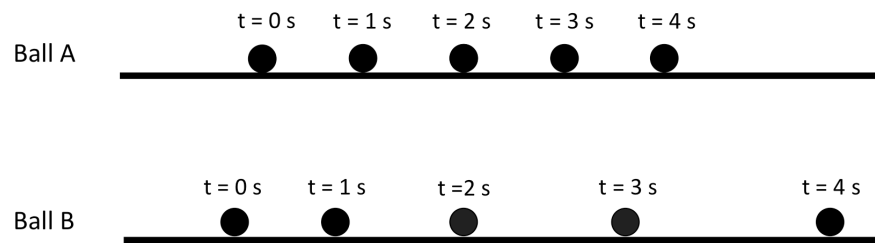


Training Problems

Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?

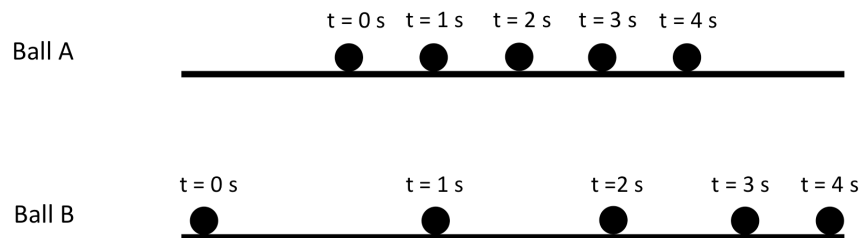


Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?



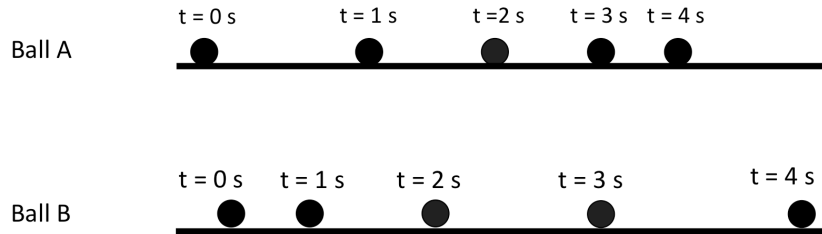
Training Problems

Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?



Training Problems

Two balls roll along the paths shown. A snapshot of the position of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?



Transfer Problem

Ball A begins riding downward in an elevator at the same time Ball B is dropped from the roof of an adjacent building. A snapshot of the balls is taken every second. At what point in time does Ball B have the same speed as Ball A?

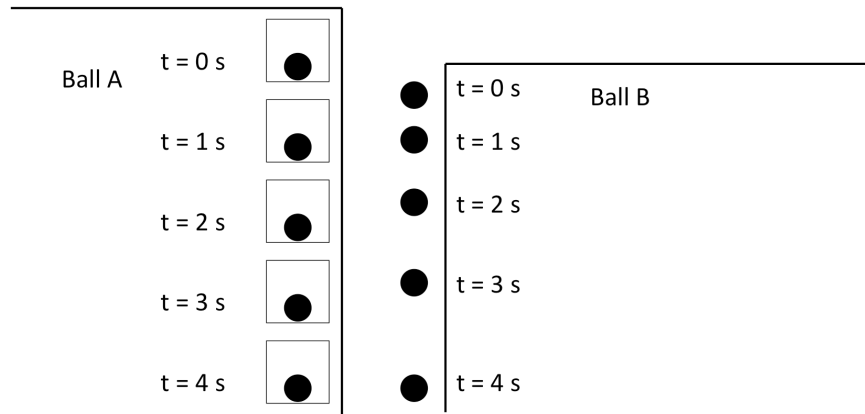
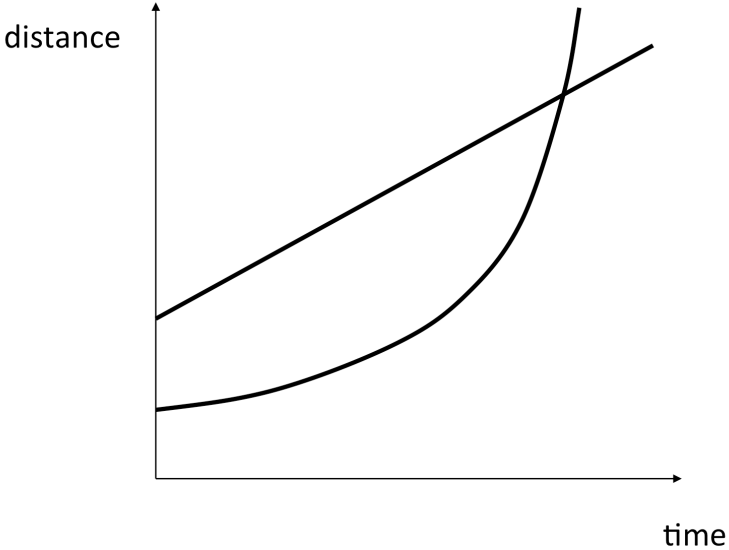
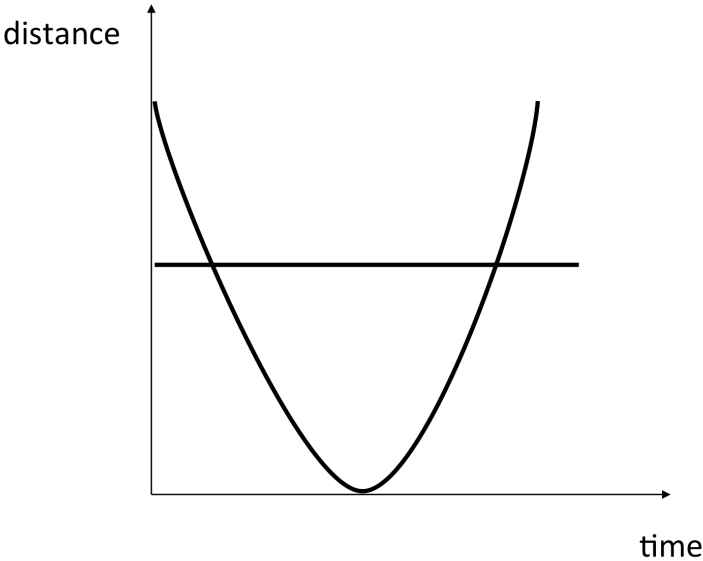
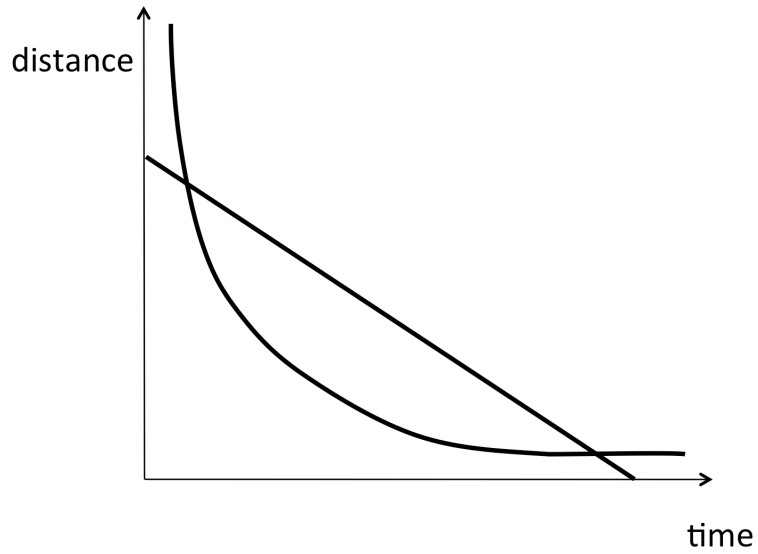


Table 6.2 The Graph problem set

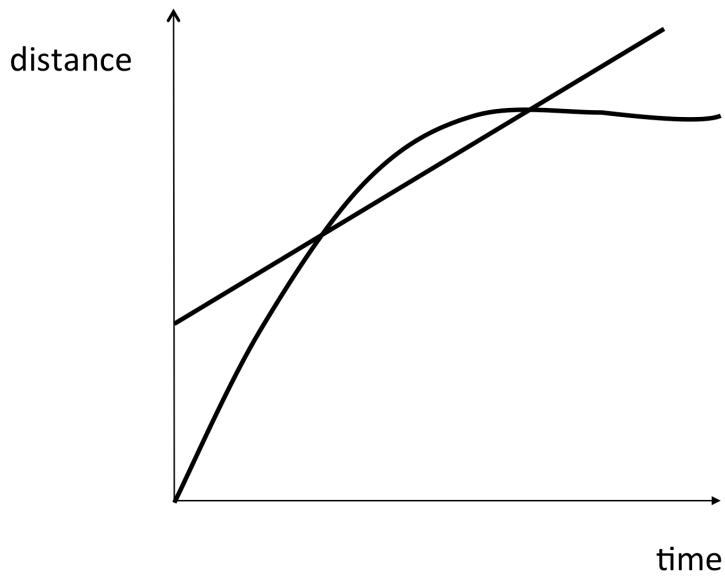
<p>Initial Problem</p>	<p>The motion of two objects is represented in the graph. When are the two objects moving with the same speed?</p>  <p>A distance-time graph with 'distance' on the vertical axis and 'time' on the horizontal axis. A straight line starts at a positive distance on the y-axis and increases linearly. A curve starts at a lower positive distance on the y-axis and increases with an increasing slope, eventually crossing the straight line.</p>
<p>Training Problems</p>	<p>The motion of two objects is represented in the graph. When are the two objects moving with the same speed?</p>  <p>A distance-time graph with 'distance' on the vertical axis and 'time' on the horizontal axis. A horizontal line is drawn at a constant positive distance. A parabola opens upwards, starting at a high distance on the y-axis, reaching a minimum distance, and then increasing, crossing the horizontal line at two points.</p>

The motion of two objects is represented in the graph.
When are the two objects moving with the same speed?

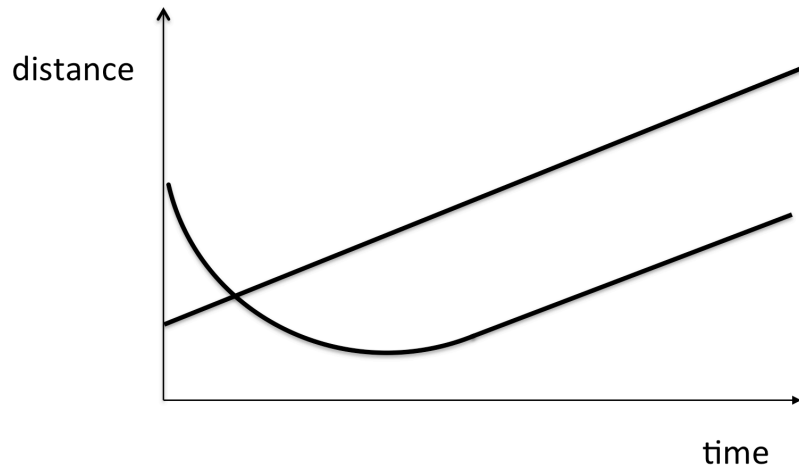


Training
Problems

The motion of two objects is represented in the graph.
When are the two objects moving with the same speed?

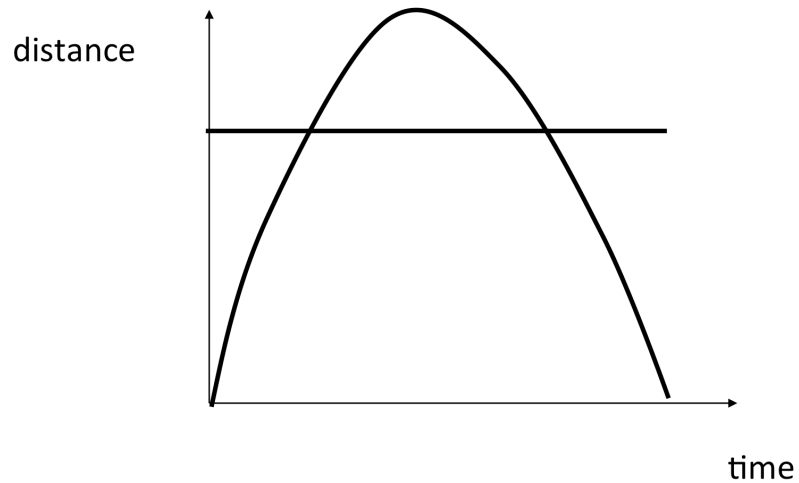


The motion of two objects is represented in the graph.
When are the two objects moving with the same speed?



Training
Problems

The motion of two objects is represented in the graph.
When are the two objects moving with the same speed?



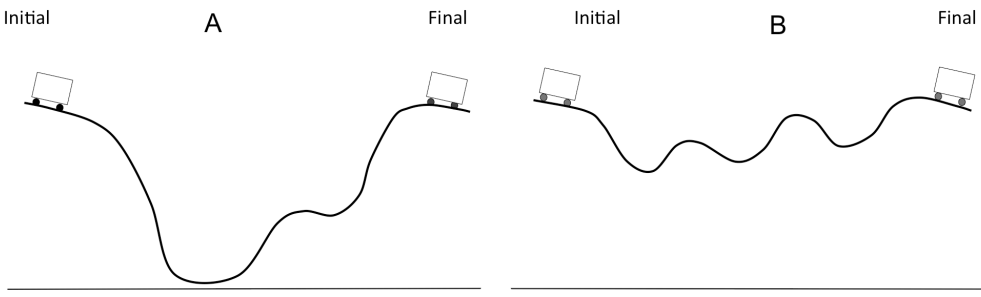
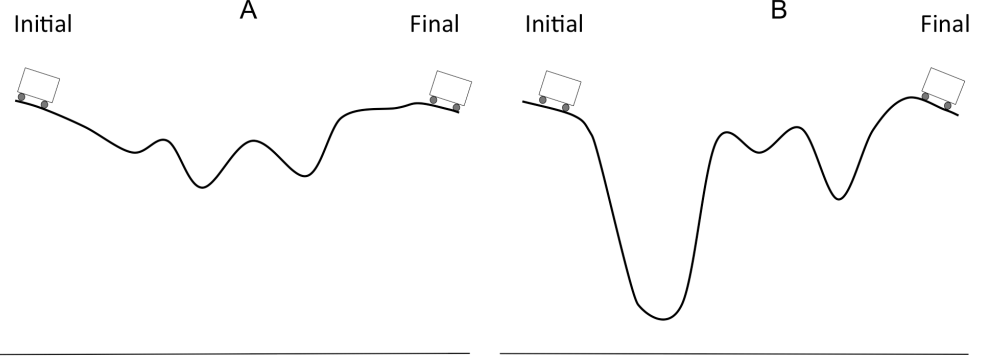
Training Problems

The motion of two objects is represented in the graph.
When are the two objects moving with the same speed?

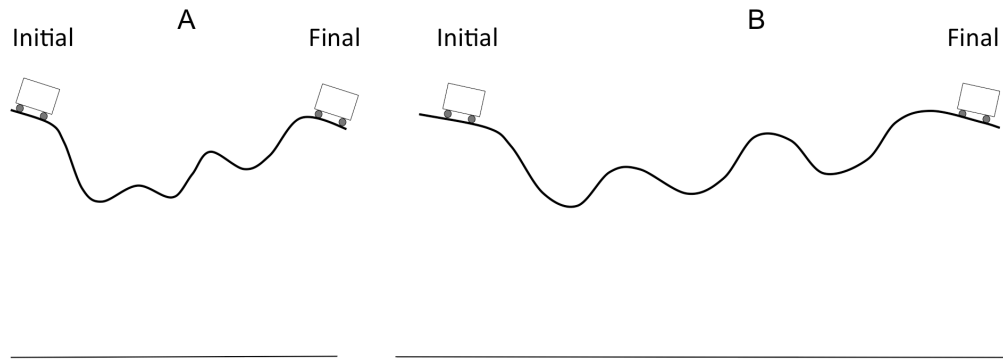
Transfer Problem

The motion of two objects is represented in the graph.
When are the two objects moving with the same speed?

Table 6.3 The Roller Coaster problem set

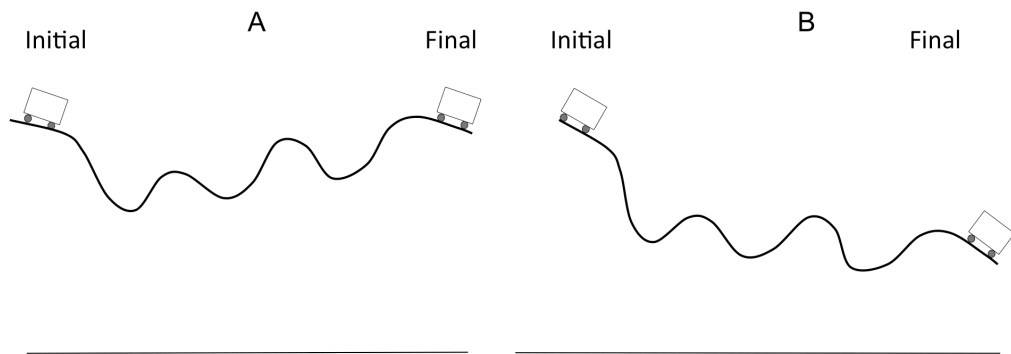
<p>Initial Problem</p>	<p>How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)</p> 
<p>Training Problems</p>	<p>How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)</p> 

How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)

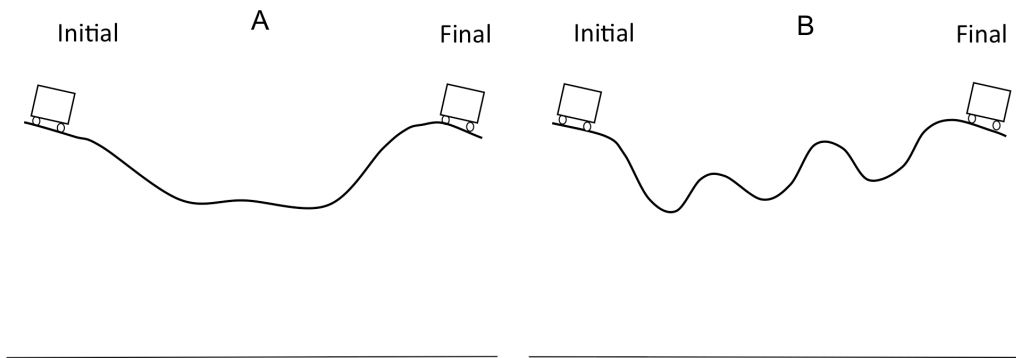


Training Problems

How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)

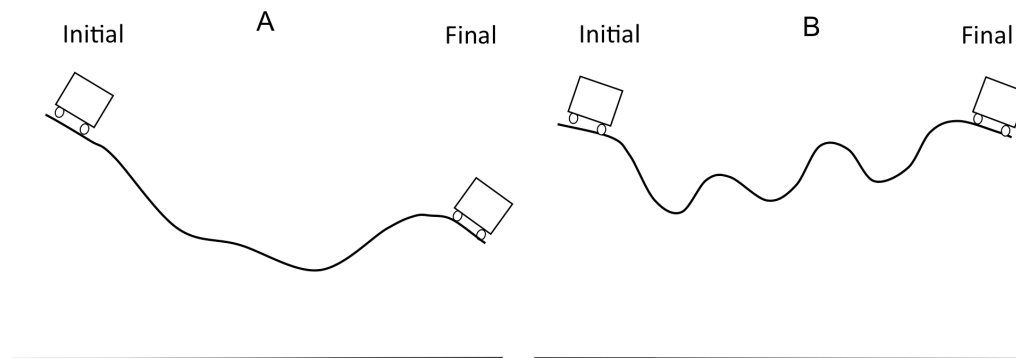


How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)



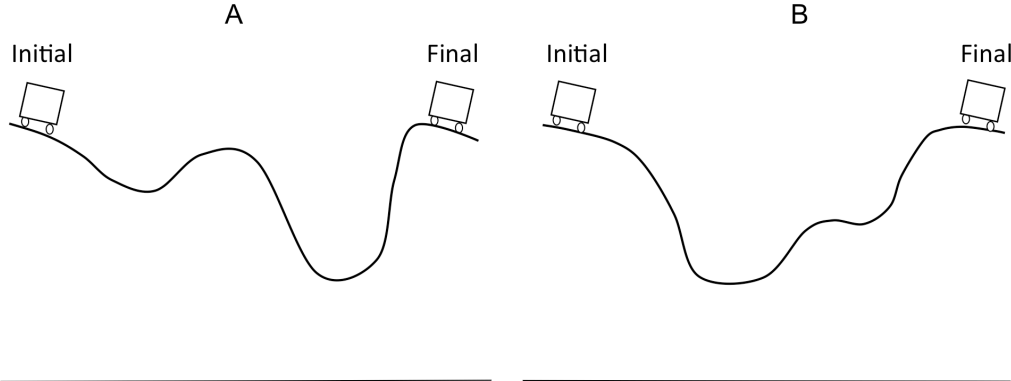
Training Problems

How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)



Training Problems

How does the final speed of cart A compare to the final speed of cart B, if the mass of the carts is the same and they both start at rest? (Frictional effects can be ignored)



Transfer Problem

Two identical balls roll down a hill. How does the final speed of ball A compare to the final speed of ball B if the masses are the same and they both start at rest? (Frictional effects can be ignored)

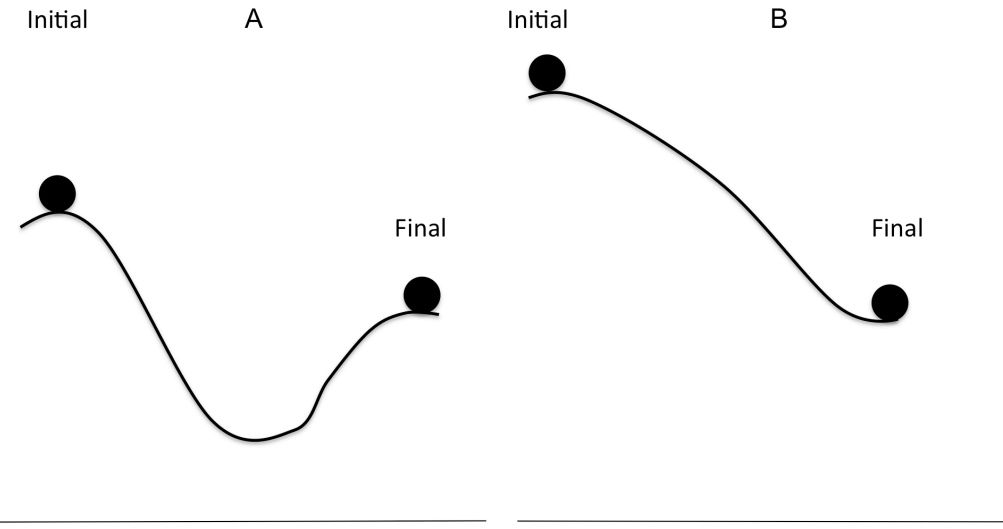
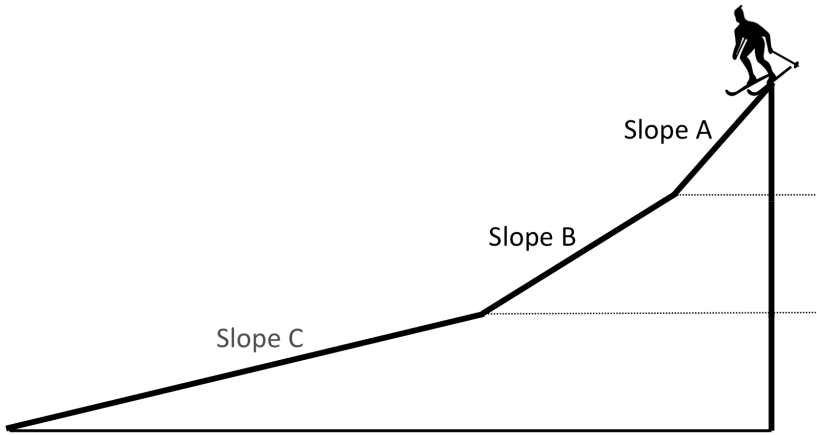
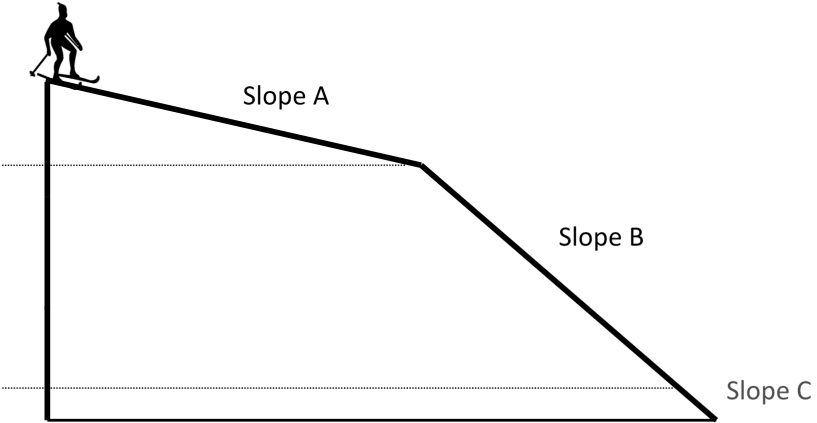
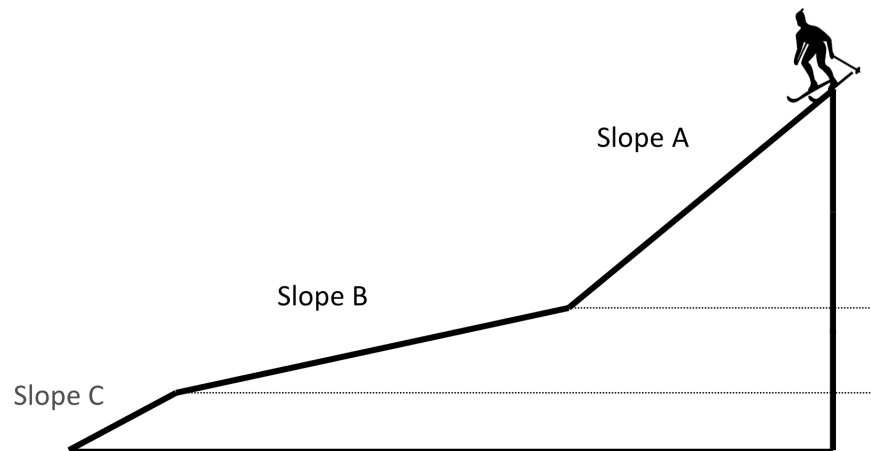


Table 6.4 The Skier problem set

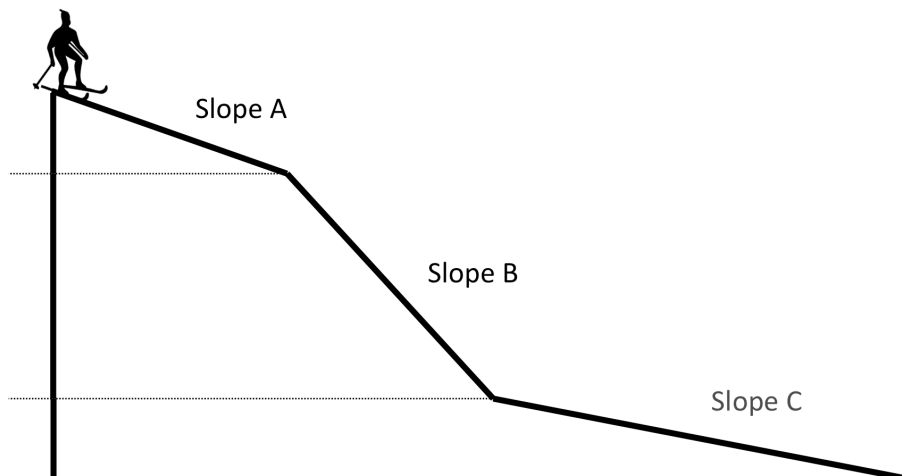
<p>Initial Problem</p>	<p>Rank the <u>changes</u> in potential energy during the skier's descent down each slope from greatest to least. (That is, rank the <u>change</u> in potential energy from the start of A to the end of A vs. the start of B to the end of B vs. the start of C to the end of C; not the total value of potential energy.)</p> 
<p>Training Problems</p>	<p>Rank the <u>changes</u> in potential energy during the skier's descent down each slope from greatest to least. (That is, rank the <u>change</u> in potential energy from the start of A to the end of A vs. the start of B to the end of B vs. the start of C to the end of C; not the total value of potential energy.)</p> 

Training Problems

Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (That is, rank the change in potential energy from the start of A to the end of A vs. the start of B to the end of B vs. the start of C to the end of C; not the total value of potential energy.)

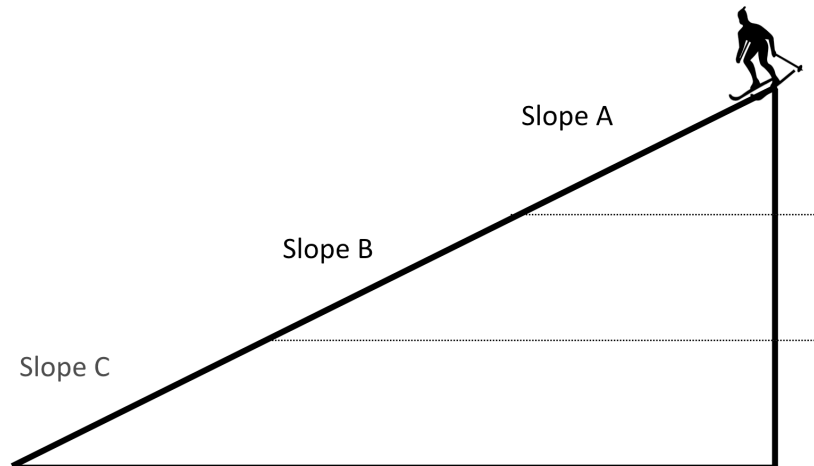


Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (That is, rank the change in potential energy from the start of A to the end of A vs. the start of B to the end of B vs. the start of C to the end of C; not the total value of potential energy.)

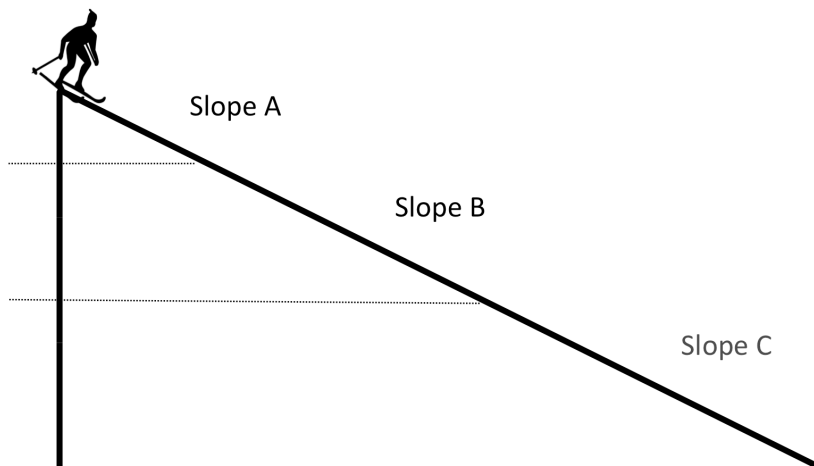


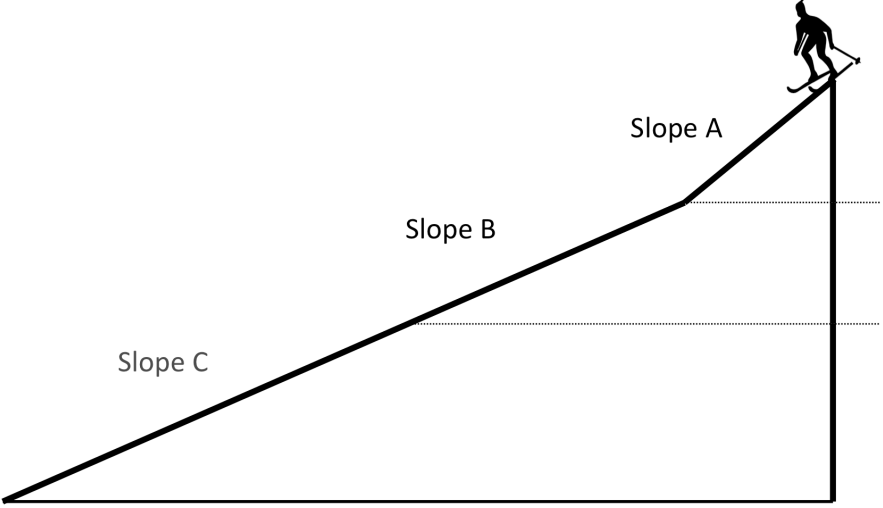
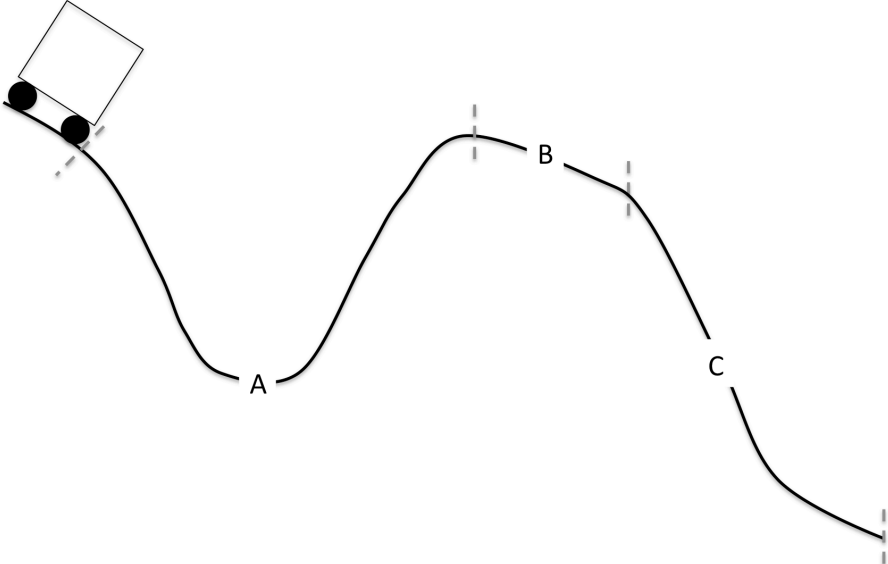
Training Problems

Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (That is, rank the change in potential energy from the start of A to the end of A vs. the start of B to the end of B vs. the start of C to the end of C; not the total value of potential energy.)



Rank the changes in potential energy during the skier's descent down each slope from greatest to least. (That is, rank the change in potential energy from the start of A to the end of A vs. the start of B to the end of B vs. the start of C to the end of C; not the total value of potential energy.)



<p>Training Problems</p>	<p>Rank the <u>changes</u> in potential energy during the skier's descent down each slope from greatest to least. (That is, rank the <u>change</u> in potential energy from the start of A to the end of A vs. the start of B to the end of B vs. the start of C to the end of C; not the total value of potential energy.)</p> 
<p>Transfer Problem</p>	<p>A roller coaster follows a frictionless track. Rank the <u>changes</u> in potential energy of the roller coaster in each section of the track from greatest to least. The dotted lines indicate the beginning and ending of each section of the track</p> <p>(Rank the <u>changes</u> in potential energy, not the total value of the potential energy.)</p> 

Appendix B - Robustness Check of Data Presented in Chapter 5 on Randomly Chosen Subsample of Observations

As indicated by Table 5.1, the some of the analyses reported in Chapter 5 contained cases in which some participants contributed only a single observation, whereas other participants contributed multiple observations, across all problem sets. This violated the ANOVA assumption of the independence of observations. To check for the robustness of our results, we carried out the analyses described in Figure 5.4 and Table 5.3 on a randomly selected subsample of the data in which no participant contributed more than a single observation. The results of these additional analyses showed the same pattern of results reported in Chapter 5—all significant main effects and interactions reported were also significant when analyzing the data from only the randomly chosen subsample.

Table 6.5 The domain relative ratio (percentage of dwell time divided by the percentage of area the AOI encompasses) in the thematically relevant area on the initial and transfer problems for a randomly chosen subsample of students who improved from the initial to transfer problem.

Randomly Chosen Subsample	Domain Relative Ratio in Thematically Relevant Area of Initial Problem (Solved Incorrectly) Mean \pm Std. Err.	Domain Relative Ratio in Thematically Relevant Area of Transfer Problem (Solved Correctly) Mean \pm Std. Err.
Cued (N=34)	4.59 \pm 0.86	8.21 \pm 0.75
Uncued (N=21)	4.67 \pm 1.11	14.96 \pm 2.51

Table 6.6 The results of a 2 (Cue vs. No Cue) x 2 (Initial vs. Transfer) Repeated Measures ANOVA comparing the domain relative ratio in the thematically relevant area of the problem diagram for a randomly selected subset of cases among students who demonstrated learning (each participant contributes only once).

Effect	F(1, 53)	p	d
Main Effect of Problem (Initial vs. Transfer)	28.19	<.001	.92
Main Effect of Condition (Cued vs. Uncued)	7.06	.010	.51
Interaction Problem*Condition	6.49	.014	--
Simple Effect of Problem (Cued Only)	4.99	.030	.54
Simple Effect of Problem (Uncued Only)	24.97	<.001	1.53
Simple Effect of Condition (Initial Problem Only)	<1	n.s.	--
Simple Effect of Condition (Transfer Problem Only)	27.64	<.001	1.00

Table 6.7 The average fixation durations (in ms) \pm 1 standard error of the mean for a randomly chosen subsample of students in the cued and uncued groups in the relevant area and entire diagram while viewing the transfer problems.

Randomly Chosen Subsample	Avg. Fixation Duration (ms) in Relevant Area -- Transfer Problem	Avg. Fixation Duration (ms) in Entire Diagram -- Transfer Problem
	Mean \pm Std. Err.	Mean \pm Std. Err.
Cued (N=34)	236.6 \pm 15.6	225.5 \pm 8.4
Uncued (N=21)	286.8 \pm 18.4	222.41 \pm 9.0

Table 6.8 The results of a 2 (Cue vs. No Cue) x 2 (Entire Diagram vs. Relevant Area) ANOVA comparing the average fixation duration on the transfer problem for a randomly selected subset of cases among students who demonstrated learning (each participant contributes only once).

Effect	F(1, 53)	p	d
Main Effect of Area (Entire Diagram vs. Relevant Area)	13.73	.001	.46
Main Effect of Condition (Cued vs. Uncued)	1.98	.165	--
Interaction Area*Condition	6.82	.012	--
Simple Effect of Area (Cued Only)	< 1	n.s.	--
Simple Effect of Area (Uncued Only)	16.14	<.001	.94
Simple Effect of Condition (Relevant Area Only)	8.96	.004	.73
Simple Effect of Condition (Entire Diagram Only)	< 1	n.s.	--