Fall 12-16-2022

Uncertainty Monitoring in Category Learning and Transfer

Rose Deng
University of Maine, rose.deng@maine.edu

UNCERTAINTY MONITORING IN CATEGORY LEARNING AND TRANSFER

By

Rose Deng

B.A. York College of The City University of New York, 2015

A DISSERTATION

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

(in Psychology)

The Graduate School

The University of Maine

December 2022

Advisory Committee:

Thane Fremouw, Ph.D., Associate Professor of Psychology, Chair

Alan Cobo-Lewis, Ph.D., Associate Professor of Psychology

Benjamin Guenther, Ph.D., Lecturer

Mollie Ruben, Ph.D., Assistant Professor of Psychology, The University of Rhode Island

J. Caleb Speirs, Ph.D., Assistant Professor of Physics, University of North Florida

DISSERTATION ACCEPTANCE STATEMENT

On behalf of the Graduate Committee for Rose Deng, I affirm that this manuscript is the final and accepted dissertation. Signatures of all committee members are on file with the Graduate School at the University of Maine, 42 Stodder Hall, Orono, Maine.

Dr. Thane Fremouw, Associate Professor of Psychology 12/16/22

LIBRARY RIGHTS STATEMENT

UNCERTAINTY MONITORING IN CATEGORY LEARNING AND TRANSFER

By Rose Deng

Dissertation Advisor: Thane Fremouw

An Abstract of the Dissertation Presented
in Partial Fulfillment of the Requirements for the
Degree of Doctor of Philosophy
(in Psychology)
December 2022

Uncertainty is commonly experienced by many people during learning and decision making. Given that many career paths require the ability to monitor uncertainty, it's important to understand how metacognitive processes influence cognitive performance. In attempts to explore how uncertainty monitoring impacts learning, three experiments were conducted. The first and second experiment utilized a categorization task in which participants explicitly learned to categorize Chemistry concepts. The third experiment assessed the impact of uncertainty monitoring on implicit learning and utilized a different task to tap into the implicit learning system. The present dissertation is one of few to investigate the role of uncertainty monitoring during explicit and implicit category learning within the context of education. Findings from Experiment 1 revealed an overall benefit of uncertainty monitoring. Performance was superior for participants who had the option to report uncertainty compared to participants who did not. Experiment 2 was designed to replicate the results from Experiment 1 and investigated other training factors and metacognitive processes that impact performance. Specifically, Experiment 2 assessed the role of feedback on performance by matching task feedback across training conditions. Additional measures of metacognition were implemented in Experiment 2 to examine participants' confidence and judgements of performance. Findings from Experiment 2 generally

supported those from Experiment 1 as it replicated the advantage of uncertainty monitoring training on task accuracy and revealed that participants' confidence and judgments of performance were influenced by a combination of training factors that help monitor and address decision uncertainty. Experiment 3 expanded upon the results from Experiments 1 and 2 and assessed whether uncertainty monitoring could also support implicit learning. Results revealed a marginal enhancement in task accuracy during the initial stages of learning; however, enhancements did not remain after learning was complete. Taken together, the present experiments suggest a general benefit of uncertainty monitoring on explicit learning and transfer. However, these benefits may be limited in supporting different types of learning, as enhancements were not as pronounced during implicit learning. This research has important implications for cognitive science and education as it highlights the benefits and limits of uncertainty monitoring on category learning.

DEDICATION

This dissertation is dedicated to my father, Deng Xue Yuan, whose sacrifices for our family are immeasurable. (這個博士學位是獻給我的父親鄧學元的，他為我們家做出的犧牲是無法估量的。謝謝你，爸爸)

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my dissertation committee: Thane Fremouw, Benjamin Guenther, Mollie Ruben, J. Caleb Speirs, Alan Cobo-Lewis, and Shawn Ell. Their time, guidance, and feedback helped make this dissertation possible.

I could not have undertaken this journey without my parents, who have worked so hard to raise my sisters and I so that we could have a better life than they did. Thank you, Mama and Baba, for always prioritizing my education and providing me with the financial means to pursue them. I am immensely proud to be a daughter of immigrants, and a first-generation college student who went on to receive a doctorate. I share this accomplishment with my family and truly could not have asked for a better support system. Thank you to my amazing sisters and best friends: Stella, Lily, Irene, and Cow, for all their encouragement, laughs, and willingness to be the guinea pigs in my research experiments.

Lastly, thank you to Charlotte and Olive, for their unconditional support and seemingly unlimited patience when “10 more minutes” turned into 2 hours.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Many real-world skills depend on the ability to monitor uncertainty. For example, airport security officers need to differentiate between safe and dangerous items. Failing to correctly categorize the item can lead to inaccurate judgments and potentially fatal outcomes. As such, a variety of domains including on-the-job training and classroom learning aim to teach fundamental categories and uncertainty monitoring. Such metacognitive abilities can help guide decision-making and support transfer of information (Paris & Winograd, 1990), especially categorical information.

A notable challenge in education is developing instructional designs that monitor student learning and promote transfer of knowledge and skills outside of the classroom. The present dissertation takes a cognitive perspective and applies theories and methods from cognitive science to fill this gap. A major theme throughout this document will be the role and extent to which uncertainty monitoring supports category learning in education, which has been underexplored. In fact, the existing literature on uncertainty monitoring is limited in the types of learning assessed. Studies have focused primarily on explicit learning, which depends on declarative memory, the knowledge that we can consciously recall. It is unclear whether uncertainty monitoring differentially impacts, or is even possible, during implicit learning, which depends on nondeclarative memory, the knowledge that we do not have conscious access to.

Investigating how people learn and make decisions under uncertainty is crucial for improving training approaches that aim to support learning. This dissertation fills gaps in both cognitive science and education literature by investigating the role of uncertainty monitoring and metacognition in learning and transfer. It aimed to answer the following questions: Does monitoring uncertainty improve category learning and transfer? To what extent can monitoring uncertainty support performance? Do metacognitive and uncertainty monitoring processes differ between explicit and implicit learning?

Category Learning in Education

Understanding the factors that impact learning is important for developing approaches that promote learning and transfer of knowledge and skills. One core skill being the ability to categorize. Categorization is the act of classifying objects and events into separate classes. It plays a critical role in our decision-making and behavior and helps us reason and make inferences about the world. Given this important skill, many disciplines require learning the key categories of each domain. For instance, geologists are skilled in classifying rock types, marine scientists with classifying phytoplankton, and virologists with classifying novel strains of a virus.

Knowledge of categories is thought to have a profound impact on how well students can learn and transfer information to new instances (Bransford & Schwartz, 1999; Gick & Holyoak, 1980; Koedinger & Roll, 2012; Rittle-Johnson, Star, & Durkin, 2009; Zimmerman, 2000). A concerning issue, however, is the accuracy of that knowledge as students may be unaware of errors and may transfer incorrect information (Koriat & Bjork, 2005; Metcalfe, 2002; 2008). Consequently, students may lack important skills and understanding necessary for performing future tasks outside of the classroom.

One way to address this is to train students to monitor their learning and uncertainty. Such metacognitive skills allow people to identify gaps in knowledge and adjust their strategies to meet the demands of novel tasks and problems (Paris & Winograd, 1990). Despite the well-established literature, uncertainty monitoring within this subfield of learning is scarce. Thus, this dissertation focused on uncertainty monitoring during category learning. It discussed the importance of metacognition and uncertainty monitoring, theories that aim to promote learning and transfer, and employed various methods to study the impact of uncertainty monitoring on performance.

Metacognition and Uncertainty Monitoring

In this dissertation, the term “uncertainty monitoring” is used to refer to components of metacognition. Metacognition refers to the knowledge and monitoring of one's own cognitive processes (Nelson & Narens, 1990; Veenman, Van Hout-Wolters, & Afflerbach, 2006). It is regarded as one of mankind’s most sophisticated cognitive capacities and is most integral to learning and academic achievement (Flavell, 1979; Brown, 1977; O’Dwyer & Childs, 2014; Regan, Childs, & Hayes, 2011; Stieff, 2011; Gersten, Jordan, & Flojo, 2005).

This higher order process involves the awareness and regulation of cognitive activities which can be distinguished by two components: regulation and knowledge of cognition. Regulation of cognition refers to the processes that help control our learning, whereas knowledge of cognition refers to what we know about our own learning (Brown & DeLoache, 1978; Jacobs & Paris, 1987; Schraw & Moshman, 1995; Veenman, 2005). This may comprise of information, categories, and strategies that help us monitor our uncertainty, and evaluate the validity of our knowledge (Flavell, 1979; Isaacson & Fujita, 2006; Metcalfe & Kober, 2005; Nelson et al., 1999).

The cognitive state of uncertainty is typically characterized by a lack of understanding or gap in knowledge. Humans, and other animals, are known to adjust their strategies and behaviors depending on the level of uncertainty experienced (Behrens et al., 2007; Nassar et al., 2012; Lee et al., 2014). Specifically, humans actively take steps to reduce uncertainty by seeking and gathering information to inform judgment and decision-making (Bruner, 1973; Chowdhury, Gibb, & Landoni, 2011; Kuhlthau, 1993). This is thought to be an indicator of greater metacognition. A pressing question in this dissertation is whether metacognitive processes support category learning and transfer, and what are some ways to promote it.

Measuring Metacognition

Metacognition and uncertainty monitoring have typically been assessed using confidence ratings and perception of performance. Students are instructed to judge their performance and report their perceived performance, which is compared to their actual performance. This is referred to as "calibration". This calibration process suggests that when differences between perception of performance and actual performance are minimal and closely matched, then good calibration exists which is indicative of greater metacognition and performance monitoring (Callender, Franco-Watkins, & Roberts, 2015; Lundeberg et al., 1994; Nietfeld et al., 2006).

In contrast, poor calibration, or calibration bias, may indicate poor metacognitive monitoring and ability. This can include overconfidence, where perceived performance is greater than actual performance, or under-confidence, where students lack confidence in their correct responses and report lower performance than actual performance. The former can lead to a false sense of mastery of materials and skills, while the latter can lead to overtraining and unnecessary practice. As such, accurate calibration is necessary for successful learning and effective resource allocation.

Importantly, calibration bias can extend beyond comparisons of task performance. It can also include the ability to assess and monitor other forms of knowledge and skills (Dentakos, Saoud, Ackerman, & Toplak, 2019). Questions in everyday life such as, “Do I need to study this chapter again?” requires accurate calibration and depends on metacognitive processes.

Such metacognitive knowledge can be correct or incorrect, with incorrect knowledge being more pervasive and resistant to change (Callender et al., 2015; Renner & Renner, 2001; Smith & Washburn, 2005; Washburn et al., 2005). For example, Figure 1 depicts the results from a study that investigated metacognitive training in the classroom. Students were given an exam and asked to rate their performance on the exam (from 0 to 100) prior to turning it in. Calibration accuracy was used as a measure of metacognition and confidence, where students’ judgments of performance were compared with their actual performance.

The experiment by Callender and colleagues (2015) reflects the key findings that much of the literature on metacognition has found, that a judgment-performance gap exists (see Figure 1, top). Specifically, lower performing students exhibit greater overconfidence and poorer judgment and monitoring of performance. This is important because knowledge and awareness about one’s own learning can impact future study choices, learning, and transfer (Callender, Franco-Watkins, & Roberts, 2015; Metcalfe & Finn, 2008).

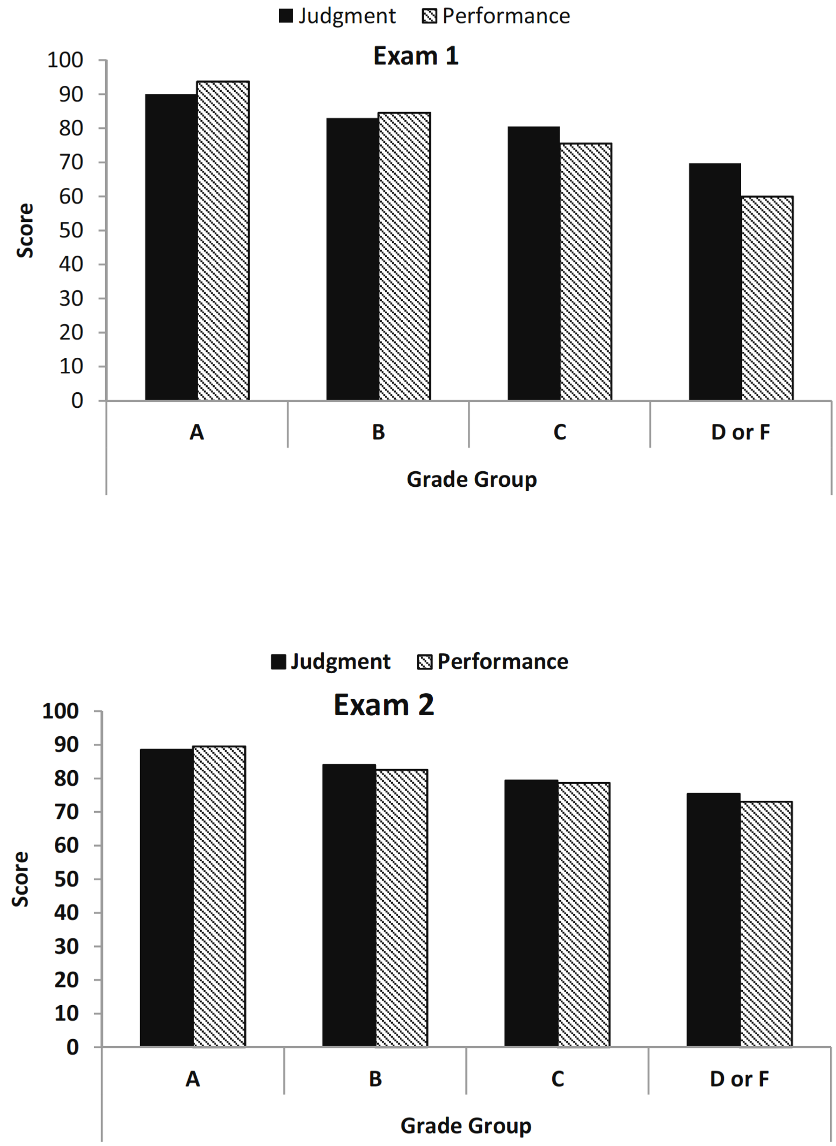


Figure 1. Results from Study 1 of Callender, Franco-Watkins, & Roberts (2015) comparing judgment and performance scores on pre-metacognitive training in exam 1 (Top), and post-metacognitive training in exam 2 (Bottom).

Limitations of Current Approaches

Despite the robust findings on the benefits of metacognition and uncertainty monitoring, traditional teaching approaches do not monitor learning in real-time and may not effectively address errors during knowledge acquisition. Instead, students are tasked with the responsibility of monitoring their own learning. Of concern is whether students are aware of when they know and understand the materials, and whether calibration is accurate.

Current teaching approaches such as student self-explanation and self-regulated learning further complicate this. For instance, self-explanation encourages students to explain information as it is learned, which is thought to benefit recall and comprehension (Ainsworth & Burcham, 2007; Chi et al., 1989; O'Reilly, Symons, & MacLatchy-Gaudet, 1998; Wong, Lawson, & Keeves, 2002). However, it can be detrimental to performance if the explanation is wrong.

The efficacy of self-regulated learning and self-explanation greatly depends upon the accuracy and awareness of knowledge and understanding (Bielaczyc, Pirolli, & Brown, 1995; Chi, Leeuw, Chiu, & Lavancher, 1994; King, 1994). These approaches at their core are dependent on students' existing metacognitive skills and abilities. Thus, not only is it important to understand how uncertainty monitoring impacts learning, but it is equally important to provide a means by which students can monitor and correct uncertainty during knowledge acquisition. Training students to monitor their learning and uncertainty may address these issues.

Categorization tasks, for example, are particularly well suited for studying uncertainty as they assess the ability to learn, apply, and transfer acquired knowledge to novel contexts. Unlike standard teaching in the classroom, categorization tasks can be used to examine students' trial-by-trial progress, monitor learning and uncertainty, and provide real-time feedback.

In addition, previous research has been limited in scope as it primarily focused on explicit learning. There is much evidence to suggest that learning and memory involves multiple neurologically distinct systems (Helie et al., 2010; Maddox, Ashby, &; Bohil, 2003; Milton &; Pothos, 2011; Nomura et al., 2007; Reber et al., 2003; Schacter, 1987; Sherry & Schacter, 1987; Squire & Schacter, 2002; Squire & Wixted, 2011). In order to improve learning and performance, it is important to consider how different types of knowledge can lead to dissociations in the systems recruited. A question in this dissertation, and in cognition literature, is whether metacognitive processes, such as uncertainty monitoring, impacts learning differently based on the system recruited.

Explicit and Implicit Learning

Different types of learning and tasks depend on qualitatively distinct processing systems (Ashby et al., 1998; Seger & Miller, 2010; Squire, 2004). For instance, explicit learning is thought to depend on a declarative system, which is characterized as learning with awareness. In contrast, implicit learning depends on a nondeclarative, procedural system, which is characterized by the absence of conscious awareness (Reber, 1967; Squire & Wixted, 2011; Tulving, 1970, 1991).

The initial stages of learning and skill development may require students to explicitly learn how to perform a task and attend to declarative knowledge. However, with practice, procedural knowledge can develop and allow the skill to be performed without declarative knowledge. That is, over time, these skills can be performed implicitly, with seemingly no conscious awareness.

Lack of awareness may result in the inability to verbally report what is learned, such as rules and strategies. Studies show that awareness and confidence are generally greater during explicit learning tasks, which may be indicative of better calibration and performance monitoring (Dienes & Berry, 1997; Schoenherr & Lacroix, 2020). Conversely, metacognition is presumed to be impaired during implicit learning, as processes are difficult to verbalize and may be hidden from conscious monitoring and evaluation. Thus, if monitoring uncertainty depends on conscious awareness, then is it even possible to monitor uncertainty during implicit tasks?

Explicit—Implicit Metacognition

Central to the metacognition literature is the dissociation between explicit and implicit processes. In general, metacognition is considered an explicit process that recruits an explicit system that is associated with executive function, self-regulated learning, and consciousness (Flavell, 1979; Rosenthal, 2000). These processes are theorized to lead to experiences and judgments that impact performance, such as tip-of-the-tongue (TOT) states and feeling-of-knowing (FOK) judgments. TOT states are characterized by the feeling that a currently inaccessible item from memory will be recalled at a later point (Brown & McNeill, 1966; Schwartz, 2008), whereas FOK judgments are characterized by the feeling that one is able to recognize an item prior to retrieval (Hart, 1965; Metcalfe, 2000; Nelson & Narens, 1990). These experiences have been used to study metacognitive monitoring and have provided insight on the cognitive and neural processes involved with metacognition and performance.

Research suggest that metacognitive monitoring and judgments may depend upon different processes (Schwartz, 2008). For instance, TOT states have been found to be more dependent on working memory resources compared to FOK. This dissociation has been observed in neuroimaging studies as well, which show differential patterns of neural activity (Maril et al., 2003; Wagner, Maril, & Schacter, 2001). Specifically, TOT judgments are associated with increase neural activity in regions involved with working memory, including the anterior cingulate, right dorsolateral, and right inferior prefrontal region (Wagner, Maril, & Schacter, 2001). In contrast, FOK judgments are associated with greater activity in the left dorsolateral, left anterior prefrontal and parietal regions (Maril et al., 2003; Kikyo & Miyashita, 2004; Kikyo et al., 2002). It is thought that these differences are due to FOK judgments operating more implicitly and unconsciously compared to TOT judgments (Koriat, 2000; Reder & Schunn, 1996). This challenges the notion that metacognitive processes are entirely explicit (Kelley & Jacoby, 1996; Reder & Schunn, 1996).

In fact, metacognitive monitoring and judgments can tap into different processes based on the demands of a task. For example, uncertainty monitoring and perceptual responding differentially depend on explicit working memory. Uncertainty responding has been shown to recruit working memory resources in both humans and non-human animals compared to perceptual responding (Coutinho et al., 2015; Smith et al., 2013). Performing a concurrent working memory task during a perceptual discrimination task can increase cognitive load and disrupt, as well as significantly reduce, uncertainty responses but not perceptual responses (Coutinho et al., 2015; Smith et al., 2013). This suggest that uncertainty responding depends upon an explicit process that places significant demands on working memory and executive attention. This is not to say, however, that uncertainty monitoring is entirely explicit. The impact of a concurrent task has been shown to reduce over time. That is, with training and practice, humans may respond to uncertainty with minimal working memory resources as judgments become easier, faster, and somewhat automatic-like. Thus, metacognitive processes may change based on the demands of the task and with repeated experience.

This is in line with other theories on metacognition, which postulate that metacognition is supported by two distinct processes: 1) an explicit, information-based process that occurs early in learning, and 2) an implicit, experience-based one that occurs later in learning (Koriat, 1997; Koriat, Nussinson, Bless, & Shaked, 2008). Information-based metacognitive judgments depend on analytic and cognitive processes that are more conscious, controlled, and explicit. In contrast, experience-based metacognitive judgments are unconscious, automatic, and implicit (Koriat, 2000; Koriat et al., 2008; Reder & Schunn, 1996). Both processes are thought to play a role in learning and performance as implicit, experience-based processes inform metacognitive judgment, while explicit, information-based processes inform conscious behavior. This suggest that not all metacognitive processes are explicit and may not require awareness.

Researchers have argued that metacognition and uncertainty monitoring may also operate on an implicit level. Feelings of uncertainty may result from implicit cues, which we only become aware of when asked about our level of certainty (Reder, 1996; Reder & Schunn, 1996). For instance, people may respond appropriately to situations without knowing or being aware that they possess specific knowledge. This unawareness, or lack of metacognition, is what makes the knowledge implicit (Dienes & Perner, 2002). Conversely, people may also be aware that they possess information and can decide more quickly that they know or do not know something, before they can even retrieve the information (Reder, 1987). This may be due to familiarity and extensive experience with performing a skill or solving a problem, which can lead to implicit, experience-based learning. For example, imagine solving a multiplication problem such as 21 x 15. Someone who is familiar with multiplication may know that they know the answer before they can produce it. This implicit, experienced-based knowledge informs metacognitive judgment, whereas explicit, information-based knowledge informs conscious behaviors (e.g., mathematical problem-solving). As such, metacognition and uncertainty monitoring may encompass both explicit and implicit abilities.

In fact, humans engage in automatic and unconscious forms of metacognition every day. Activities such as riding a bike or driving a car requires constant monitoring of one's behavior and surroundings. Such implicit metacognition may guide behavior without ever reaching conscious awareness (Brinck & Liljenfors, 2012; Dienes & Perner, 2002). However, despite research suggesting that both explicit and implicit processes are involved with learning, studies on metacognition have exclusively looked at tasks that are dependent on explicit, declarative memory. It is currently unclear whether metacognitive processes also benefit learning in tasks that are dependent on implicit, nondeclarative memory.

Multiple Learning Systems

Understanding whether uncertainty monitoring differs across different types of tasks is crucial for identifying methods to best support certain types of learning. In fact, differences in instructional approaches have been shown to lead to dissociations in performance during tests of explicit and implicit knowledge. An example of this is found in the multiple-systems model of category learning (Ashby et al, 1998). According to this multiple-systems framework, different learning strategies compete between systems. An explicit verbal system is initially activated during the early stages of learning, presumably because it's controlled by consciousness. Over time, however, the strategy and system that best supports performance will eventually dominate (Ashby et al., 1998). This aligns with the dual-process framework of metacognition, which posits that metacognitive processes operate on the output of different learning systems. Metacognitive abilities such as uncertainty monitoring and self-evaluation is critical for acquiring and utilizing optimal strategies during explicit and implicit learning tasks. Research parallel to this, from the field of categorization, have developed tasks to investigate these systems and serve as a valuable tool to study these dissociations.

As such, the present dissertation uses category learning as tool to investigate uncertainty monitoring and learning within the explicit and implicit systems. Of relevance is a seminal study by Shepard, Hovland, and Jenkins (SHJ) (1961), which explored people's capacities to learn category structures that varied in complexity, rules, and strategies (e.g., explicit and implicit) (see Figure 2). Previous research, including neuroimaging studies, have provided strong support for the use of SHJ category structures to study explicit-implicit dissociations in learning (Smith, Minda, Washburn, 2004; Smith et al., 2012; Waldron & Ashby, 2001), as well as the existence of separate learning systems that are functionally and neurologically dissociable (Milton & Pothos, 2011; Nomura et al., 2007; Reber, Gitelman, Parrish, & Mesulam, 2003).

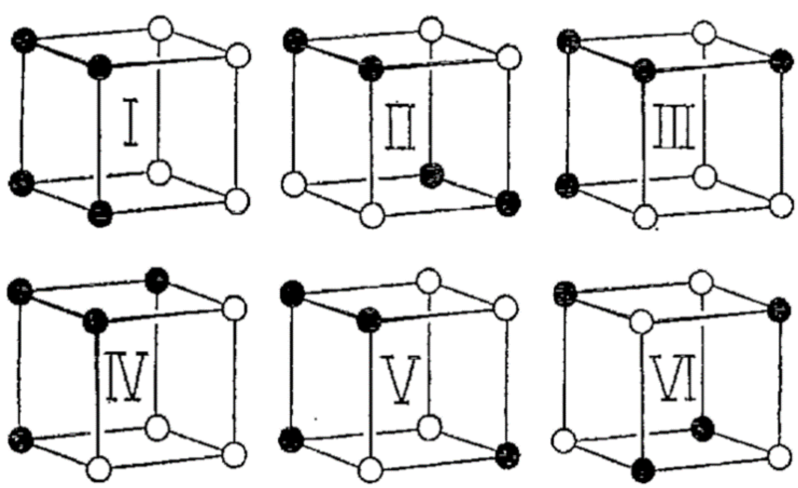


Figure 2. Structures from Shepard, Hovland, & Jenkins (1961).

A study by Minda, Desroches, & Church (2008) investigated the impact of concurrent working memory tasks on learning SHJ category structures that could or could not be easily verbalized (see experiment 2 of Minda, Desroches, & Church (2008)). Participants had to learn one of four SHJ category structures (Types I, II, III, IV, Figure 2), and classify stimuli while performing one of three concurrent tasks. These tasks included:

1) A verbal concurrent task that required participants to perform a coarticulation task, which is thought to be dependent on verbal working memory.

2) A nonverbal concurrent task, which required participants to tap their finger whenever they saw a specific stimulus.

3) No concurrent task, where participants were only instructed to learn to classify stimuli.

It was assumed that if any of the SHJ category structures depended on an explicit learning system, then performing a verbal concurrent task would interfere with learning rules and structures that also depended on the same working memory and explicit systems. The authors found that a verbal concurrent task was able to impair learning of all the category structures except Type IV. This suggests that learning Type IV categories may not require explicit, verbal working memory, but rather depend more on implicit processes, which is consistent with a multiple systems framework.

Additionally, while it is assumed that implicit learning is difficult to verbalize, it does not mean that uncertainty monitoring does not occur. For example, a study by Paul, Boomer, Smith, and Ashby (2011) investigated participants' access to uncertainty monitoring processes during tasks that depended on the explicit and implicit learning systems. They used an uncertainty monitoring paradigm that incorporated both explicit and implicit category structures that have been shown to tap into those systems (see Figure 3). Participants were instructed to make one of two primary responses based on the category membership of a stimulus or select the "uncertain" response option. In Experiment 1 and 2, they found that when participants were given the option to make “uncertain” responses on an implicit task, participants did so adaptively on difficult trials when category membership was unclear. As such, task accuracy and uncertainty responding were positively correlated as participants strategically used the “uncertain” response option to skip difficult trials while still maintaining an acceptable level of task accuracy.

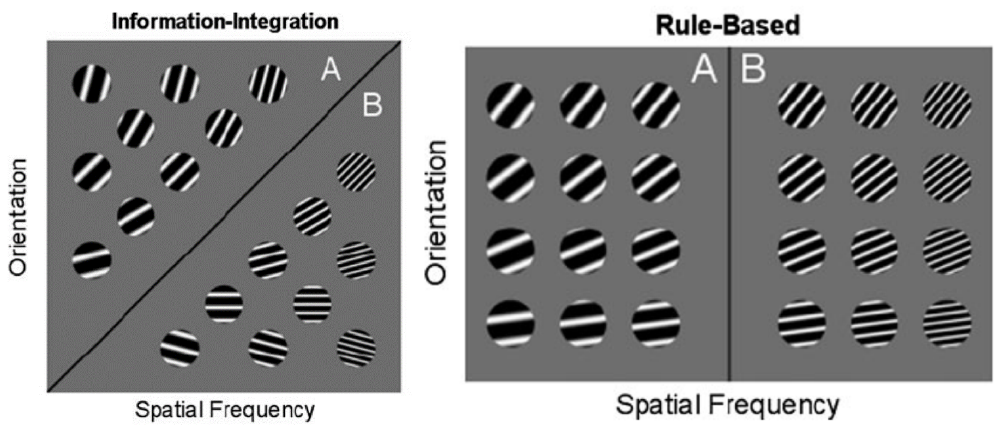


Figure 3. Example stimuli from Paul, Boomer, Smith, and Ashby (2011). (Left) Implicit, information-integration task; both dimensions (e.g., orientation and spatial frequency) were relevant for correct categorization. (Right) Explicit, rule-based categorization task, single relevant dimension (e.g., spatial frequency) for categorization.

Paul and colleagues (2011) used decision-bound models to verify participants' decision strategies and found that participants who frequently used the "uncertain" response option during the implicit task also used a suboptimal strategy (e.g., explicit strategy). In contrast, those who rarely used the “uncertain” response option used the most optimal strategy (e.g., implicit strategy). Such metacognitive processes appeared to have changed the qualitative nature of the implicit task into an explicit task. This may be because participants who were initially trained with easy-to-categorize stimuli may have discovered and applied simple rules that succeeded. When more complex and difficult stimuli were introduced, participants continued to perseverate on the simpler rule and responded with “uncertain” to avoid difficult trials while still maintaining accuracy. In this case, uncertainty monitoring during an implicit task was possible; however, allowing participants to respond with “uncertain” may reduce the likelihood of participants learning the optimal strategy, and may shift the focus of the task from an implicit learning system to an explicit one instead.

Although findings by Paul and colleagues suggest that uncertainty monitoring can occur during implicit tasks, it is unclear whether uncertainty monitoring is effective in supporting implicit learning. Contrary to the authors’ predictions, participants were able to monitor their uncertainty during an implicit learning task but effectively changed the nature of it in the process—from implicit to explicit. The question remains as to whether uncertainty monitoring benefits different types of learning, and if so, to what extent can it support learning?

Transfer of Knowledge

Typically, the goal of training and teaching approaches is to promote transfer of knowledge. Transfer occurs when learning within a certain context has an impact beyond the original training context. For example, when previously learned information improves performance in another context, it is considered *positive* transfer; however, if performance is impaired then it is considered *negative* transfer.

The extent to which learning can support future performance is classified as either *near* or *far* transfer. When learning is transferred between closely related or similar contexts, it is referred to as *near* transfer. For example, knowing how to snowboard can help with learning how to skateboard. However, if learning is transferred between contexts that appear remote and different, then it is referred to as *far* transfer. For example, understanding the concept of force in Physics, and transferring that knowledge to learning how to do tricks on a skateboard.

In the classroom, students are expected to learn and build skills that are transferable to other domains (Saetrevik, Reber, & Sannum, 2006; Taber, 2014). However, it is difficult and rare that students can transfer knowledge outside of the original training context. This may be due to several reasons including time between training and transfer, or relation and similarity between contexts. In fact, there is little agreement in the field of cognition and education about the nature and extent to which transfer occurs, other than that it rarely does (Barnett & Ceci, 2002; Detterman, 1993; Schooler, 1989). One might reasonably ask, then what is the purpose of training if transfer is not guaranteed? The answer depends on one's definition and interpretation of successful transfer. For instance, one might interpret how often a learned skill or behavior is applied as an indicator of successful transfer, while others may view the quality and effectiveness of applied knowledge as successful transfer.

The transferability of learning itself is regarded as an indicator of effective training. Different approaches and methods, such as monitoring and correcting uncertainty, are critical for promoting transfer. Consequently, significant investments of time, money, and research is put into training students on general skills that transfer beyond the classroom.

Methods to Promote Transfer

Researchers have attempted to conceptualize the process leading to successful transfer. They posit that students need to first recognize that acquired knowledge is relevant to a new context. Second, students need to be able to recall that knowledge and third, they need to be able to apply it to the new context (Barnett & Ceci, 2002). The first two steps are thought to be driven by retention of knowledge (e.g., recognizing and recalling relevant information), whereas understanding enables the third step. This proposed three-step process is thought to depend on the student's ability to recall, analyze, and process the information.

Of concern, however, is whether students know when to apply prior knowledge and whether that knowledge is correct. Knowing when to transfer information and assessing the validity of that information is equally important as the act of transferring itself. An understanding of what skills and knowledge are necessary and relevant to a specific context is critical for successful transfer.

Given that it is rare that we ever encounter identical situations, understanding how people approach, and monitor uncertainty is important for developing training approaches that support learning and transfer. This dissertation fills gaps in both categorization and education literature by investigating the role of uncertainty monitoring and metacognition in category learning and transfer. It utilized methods from cognitive science to answer the following questions: Does monitoring uncertainty improve category learning and transfer? To what extent can monitoring uncertainty support performance? Do metacognitive and uncertainty monitoring processes differ between explicit and implicit learning?

CHAPTER 2

EXPERIMENT 1

Background

A common goal in both education and cognitive science is to understand how uncertainty decreases and how certainty develops throughout the course of learning. Categorical knowledge acquired in the classroom is crucial for supporting future performance. For example, a student working in a Chemistry lab may need to draw upon classroom knowledge about hazardous chemical categories, and correctly apply that knowledge to a new setting. Lacking adequate prior knowledge or unknowingly possessing incorrect categorical knowledge can be detrimental.

Metacognition and uncertainty monitoring have been shown to be effective in facilitating transfer of learning (Paris et al., 1988; Paris & Winogran, 1990; Ricky & Stacy, 2000; Vaidya, 1999). Experiment 1 aimed to explore the role of uncertainty monitoring on category learning within the context of education. It aimed to address some of the challenges that come with developing instructional designs to monitor learning and promote transfer.

The experiment incorporated methodologies from cognitive science to train students to monitor their learning and investigated whether uncertainty monitoring could improve performance. It utilized a category learning paradigm to teach students Chemistry concepts and provided real-time, immediate feedback during training. Participants performed a classification task and learned to classify stimuli into two contrasting categories (e.g., Acidic vs. Basic). Participants were randomly assigned to learn with or without an option to report uncertainty. The additional "uncertain" response option allowed participants to monitor and address their uncertainties during training and received feedback to guide learning (Barnett & Ceci, 2002; Butler et al., 2013; Pashler et al., 2005).

In order to examine the extent to which training promoted transfer, participants were tested on a different categorization task using different stimuli. The test stimuli retained the same categorical rules and diagnostic features as those used in training but were visually different. Successful transfer to a similar, but novel and non-identical situation, was indexed by participants' knowledge of which stimuli features corresponded with which categories during test phase.

If transfer depended upon the ability to monitor learning and uncertainty, then participants who were given the option to report uncertainty would evidence greater test phase performance. Typically, metacognition is measured by comparing participants' confidence and judgments of performance with their actual performance. Accurate calibration is thought to be indicative of greater uncertainty monitoring (Callender, Franco-Watkins, & Roberts, 2015; Lundeberg et al., 1994; Nietfeld, Cao, & Osborne, 2006). Thus, participants who were given the option to monitor their uncertainty were predicted to be more confident in their responses and more accurate in their judgments of performance. The results from Experiment 1 help elucidate the role of uncertainty monitoring in the context of category learning in education.

Method

Participants

Sixty-three undergraduate college students (*N* = 63)[1] from the University of Maine were recruited from the department of psychology's research pool to participate online via Qualtrics Survey. All participants received partial course credit for participation. Participants were

[1] An initial *n* of 30 per condition was chosen as a conservative estimate based on previous literature on monitoring knowledge and uncertainty (Koriat & Bjork, 2005; Paul, Boomer, Smith, & Ashby, 2011; respectively).

randomly assigned to one of two training conditions: Uncertainty Monitoring condition (n = 33) and Forced Response Condition (n = 30). A total of 6 participants were excluded from analysis because they were statistical outliers (i.e., more than 3 SD from the mean on both average training accuracy, and accuracy during the final block of training). The remaining sample size by condition was Uncertainty Monitoring (n = 29) and Forced Response (n = 28).

Stimuli

The stimuli consisted of different objects varying in pH levels[2] and category membership (e.g., Acidic or Basic). Forty stimuli (20 per category) were used for each of the two blocks in the training phase. All training stimuli were outlined by different colors that corresponded with the object's pH level. Category membership was determined by the color of the outline of the training stimulus (e.g., Acidic = reds, yellows, and lighter shades of green; Basic = darker shades of green, blues, and purples). A novel set of forty stimuli (20 per category) were used during test phase to assess learning and transfer of categorical knowledge. All test stimuli had the same categorical rules and features as those used in training, but the objects changed and were visually different.

Procedure

In the instructions, participants were told to imagine that they were training to be Chemists. They were instructed to maximize accuracy and were informed that information learned during the training phase would be necessary for the test phase.

[2] pH is a quantitative measure of how acidic or basic an object is.

Uncertainty Monitoring Condition

During the training phase, participants in the *Uncertainty Monitoring* condition were shown a single stimulus on the center of the screen and were instructed to either sort it into one of two contrasting categories (e.g., Acidic or Basic) or respond with “uncertain” (right, Figure 4A). If participants selected the Acidic or Basic category options, they received verification feedback (e.g., “CORRECT: Acidic” or “WRONG: Acidic”) (see Figure 4B). However, if participants selected the “uncertain” option, they received feedback which consisted of the correct answer and a brief caption elaborating on the answer (e.g., This belongs in the Acidic category because it has a pH of 6.5 and has a light green outline) (see Figure 4C). Participants were told that selecting the correct answer or “uncertain” option would allow them to proceed to the next trial, but an incorrect answer would result in a 10 second “timeout” which delayed the start of the next trial.

Forced Response Condition

Participants in the *Forced Response* condition were also shown a single stimulus on the screen and were instructed to sort it into one of the two contrasting categories (e.g., Acidic or Basic). Unlike the Uncertainty Monitoring condition, however, participants in the Forced Response condition were not provided the “uncertain” response option. Participants in this condition received verification feedback for their responses (e.g., “CORRECT: Acidic” or “WRONG: Acidic”) (see Figure 4B), and were told that correct answers would allow them to proceed to the next trial, but incorrect answers would result in a 10 second “timeout” which delayed the start of the next trial.

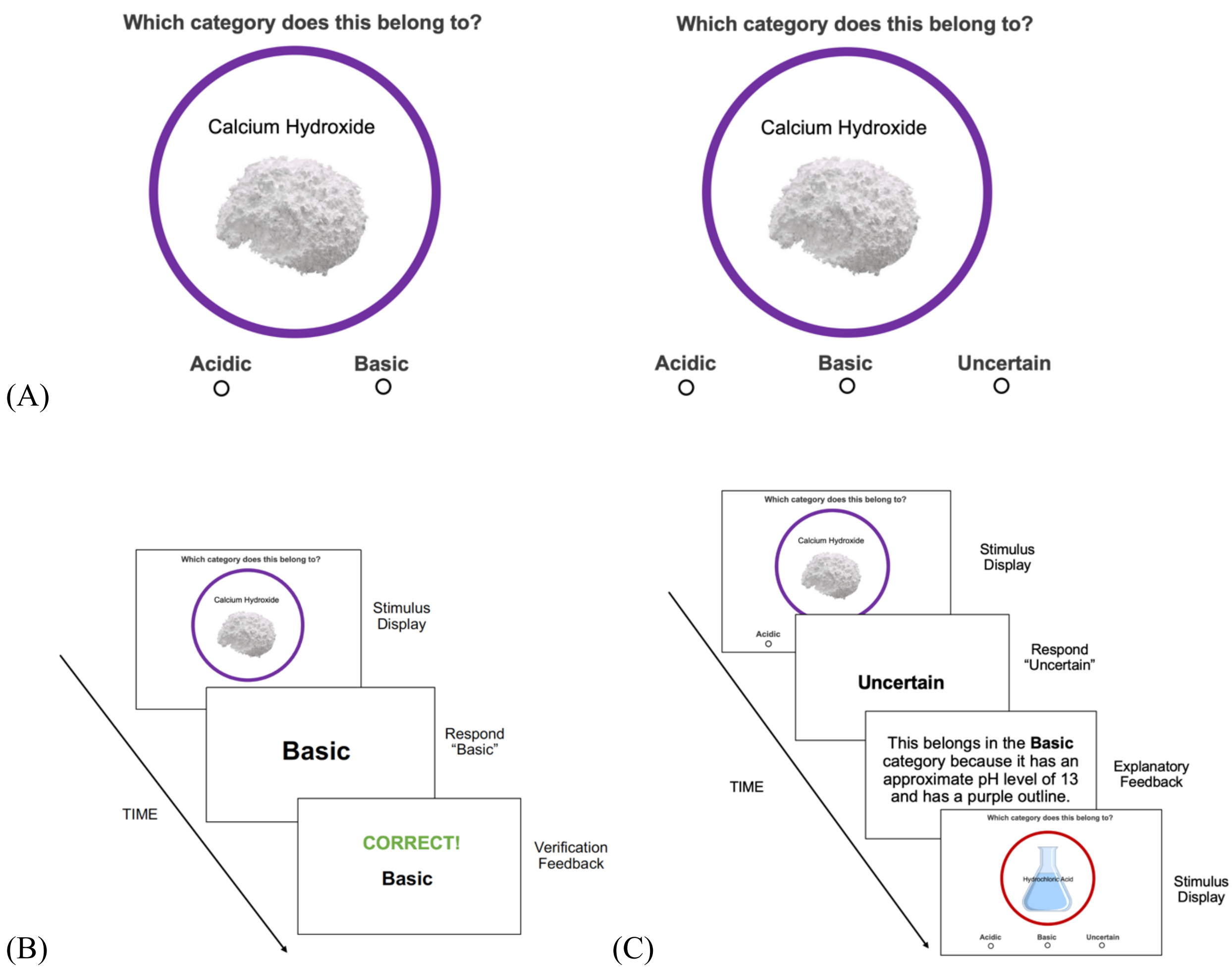


Figure 4. Example displays for two training conditions in Experiment 1: (Top row, A) Forced Response and Uncertainty Monitoring, respectively. (Bottom left, B) Verification feedback for category response. (Bottom right, C) Explanatory and elaborative feedback for uncertain response option in the Uncertainty Monitoring training condition.

After participants completed the training phase, they were tested on a novel task with a novel set of stimuli. Participants were told that they would be doing a virtual litmus test and there would be an image of a rectangular shaped paper in a virtual beaker. They were informed that the paper would change colors according to the type of liquid in the beaker. Participants were instructed to determine the type of liquid that was in the beaker (e.g., Acidic or Basic) and estimate the pH level of the liquid (see Figure 5). After each test trial, participants were prompted to report their confidence in their response on a Likert-type scale ranging from 1 (Not at all Confident) to 7 (Extremely Confident). Participants were not given an “uncertain” response option and were not provided any feedback during test phase. The goal of the test phase was to assess participants’ ability to transfer learned information to a novel context, where the task question and stimuli appeared different, but the demands of the tasks were the same.

After the test phase, participants completed a brief post-task questionnaire regarding the information learned, and their confidence and decision-making throughout the experiment. The post-task questionnaire also included an attention check question to ensure data quality and engagement of participants (see Appendix A).

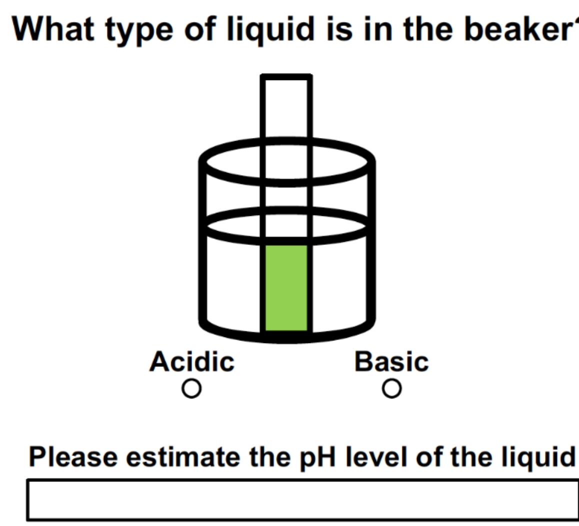


Figure 5. Example display during test phase for both training conditions.

Data Analysis Procedure

Average performance across training blocks were calculated to examine learning curves. To accurately assess learning, average scores per training block were adjusted for participants within the Uncertainty Monitoring condition. This approach was used to account for participants' "uncertain" responses during training, as selecting this option did not indicate a correct nor incorrect categorical response. Therefore, "uncertain" response trials were excluded from performance accuracy calculation. Adjusted scores for participants in the Uncertainty Monitoring condition only included trials that participants made categorical responses to (e.g., responding with category A or B). Subsequent analyses were conducted on adjusted scores and results throughout this dissertation report on adjusted scores for the Uncertainty Monitoring condition.

In order to assess whether uncertainty monitoring could support learning, a two-way ANOVA was conducted to examine the effect of training method (Uncertainty Monitoring vs. Forced Response) and time (Block 1 vs. Block 2) on performance during training phase. Independent samples t-tests were conducted to examine the effect of training method on confidence and transfer performance during test phase.

Results

Training Phase: Task Performance

Performance generally improved across training blocks for both conditions with higher training accuracy observed in the uncertainty monitoring condition (Figure 6). This observation was supported by a 2 training method (uncertainty monitoring vs. forced response) x 2 time (block 1 vs. block 2) ANOVA that revealed a significant main effect of training method [$F(1, 55) = 10.637$, $p = .001$, $\eta p^2 = .08$] and time [$F(1, 55) = 39.11$, $p < .001$, $\eta p^2 = .243$] on performance during training. Indicating that performance improved over time and that uncertainly monitoring resulted in higher performance.

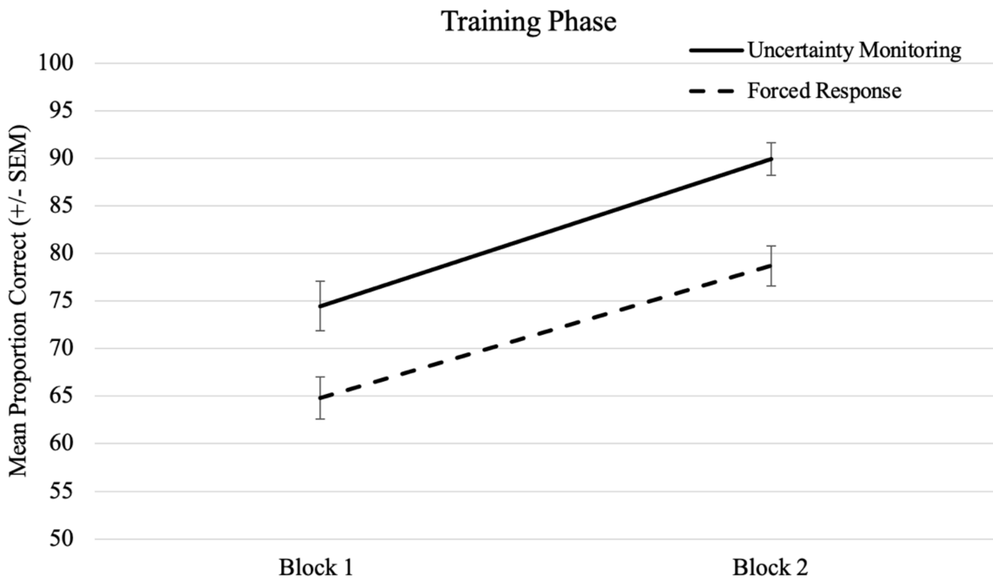


Figure 6. Performance for both training conditions during training phase on category accuracy. Figure depicts adjusted scores during training phase for the Uncertainty Monitoring condition.

Test Phase: Task Performance

Inspection of the test data suggests that participants in both training conditions were generally able to transfer knowledge from training phase to test phase (Figure 7). Specifically, independent samples t-test show that the Uncertainty Monitoring condition performed significantly better on category accuracy during test phase compared to the Forced Response condition [$t(48.36) = -2.12$, $p = .039$, $g = .556$][3]; however, participants' ability to estimate the pH levels of test stimuli did not differ between conditions [$t(52) = .176$, $p = .861$, $g = .05$] (Figure 8).

[3] Levene's test indicated unequal variances, degrees of freedom were adjusted.

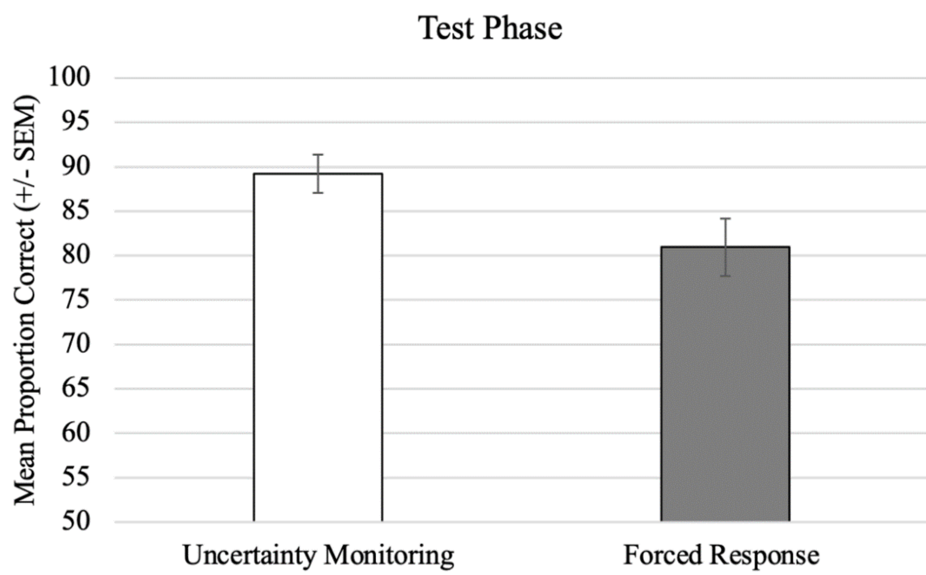


Figure 7. Performance for two training conditions during test phase on category accuracy. Figures depict adjusted scores during training phase for the Uncertainty Monitoring condition.

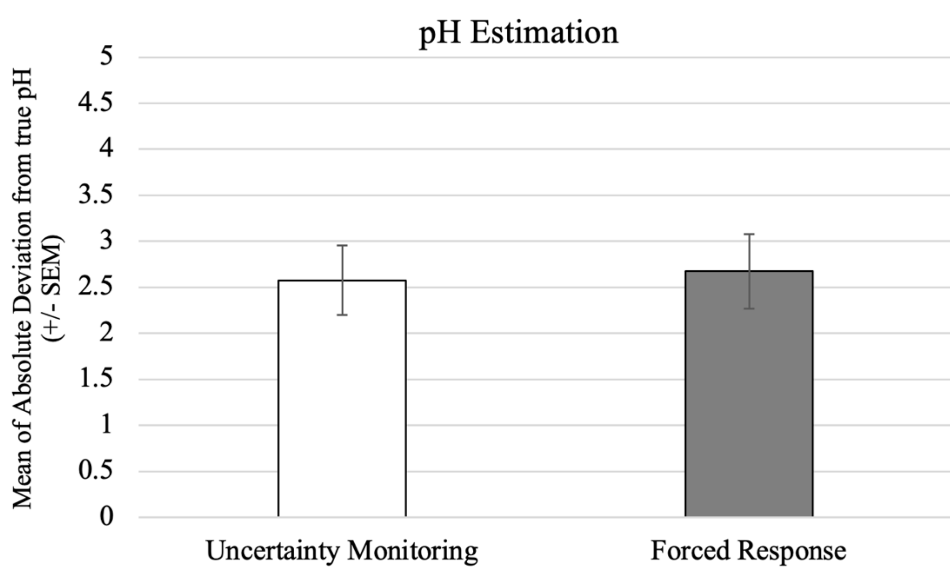


Figure 8. Performance on estimating pH levels of test stimuli. Average error per trial was computed by taking the absolute deviation from the true pH value. Lower scores indicate better accuracy.

Test Phase: Confidence

Confidence was found to be a moderate significant predictor of test accuracy for both training conditions, as confidence accounted for a significant proportion of test performance in the Uncertainty Monitoring [R^2 = .404, F(1, 27) = 18.303, p < .001] and Forced Response [R^2 = .296, F(1, 27) = 11.33, p = .002] training conditions (see Table 1 and Figure 9); however, no group differences were observed for response confidence [t(56) = -.789, p = .433] (Figure 10).

Table 1. Regression Analysis summary for confidence predicting test accuracy in Experiment 1.

		Unstandardized Coefficients		Standardized Coefficients		
Training Condition	***df***	**B**	***SE***	**β**	***t***	***p***
Uncertainty Monitoring Condition	27	4.979	1.164	0.636	4.278	0.000
Forced Response Condition	27	6.489	1.927	0.544	3.367	0.002

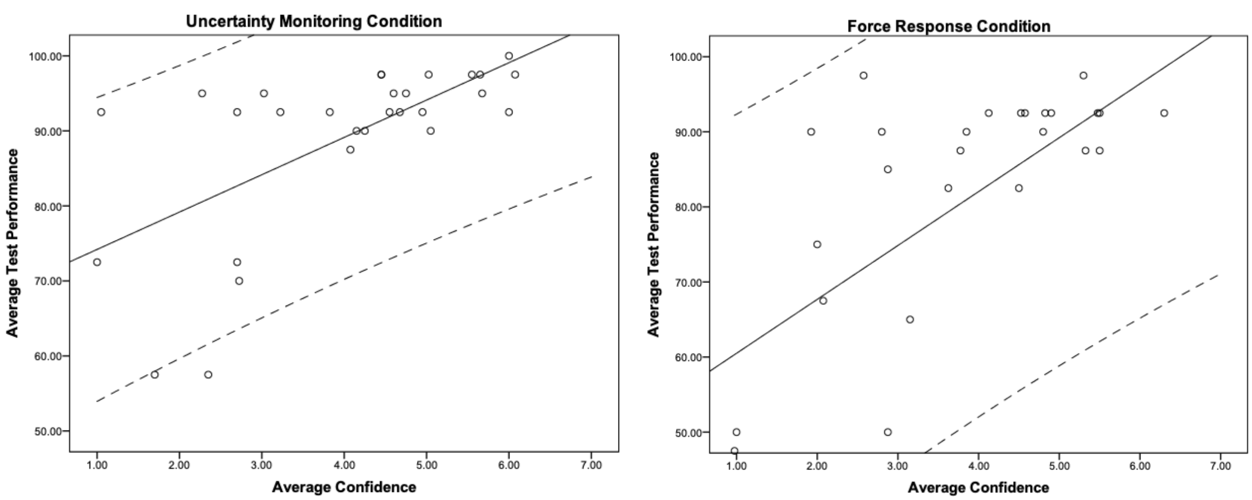


Figure 9. Average test phase accuracy by average confidence between: (Left) Uncertainty Monitoring condition, and (Right) Forced Response condition. Dashed lines represent 95% confidence interval bands.

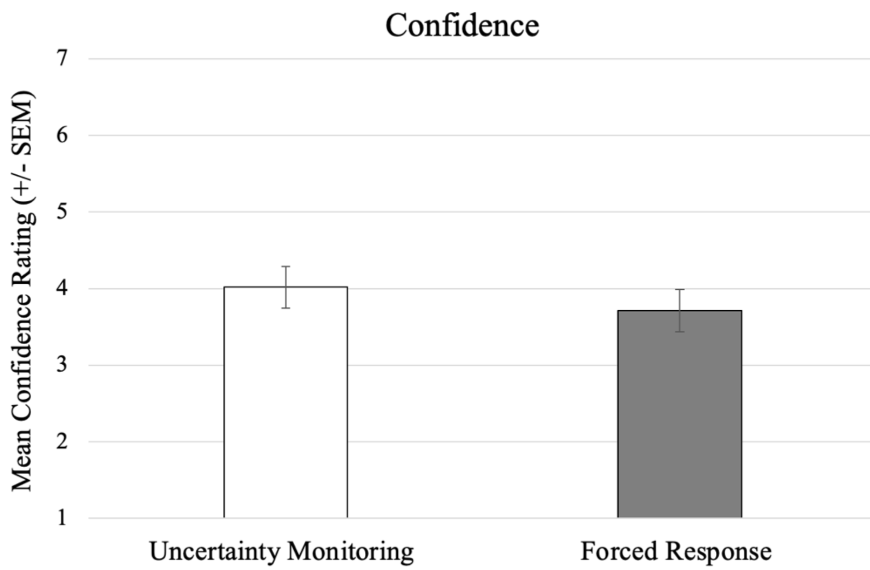


Figure 10. Average confidence rating during test phase.

Uncertainty Monitoring Training

A primary question in Experiment 1 was the role of uncertainty monitoring on performance. Specifically, how participants utilized an uncertain response option and its impact on learning and transfer. A paired samples t-test examined participants' uncertainty responses between blocks 1 and 2 of training. It indicated a significant decrease in percentage of "uncertain" responses throughout the course of training for participants in the Uncertainty Monitoring condition [$t(28) = 4.56$, $p < .001$, $g = .934$, Figure 11].

In sum, these data suggest that participants were generally able to learn and transfer knowledge to both novel stimuli and tasks, with performance being greater for participants trained in the Uncertainty Monitoring condition.

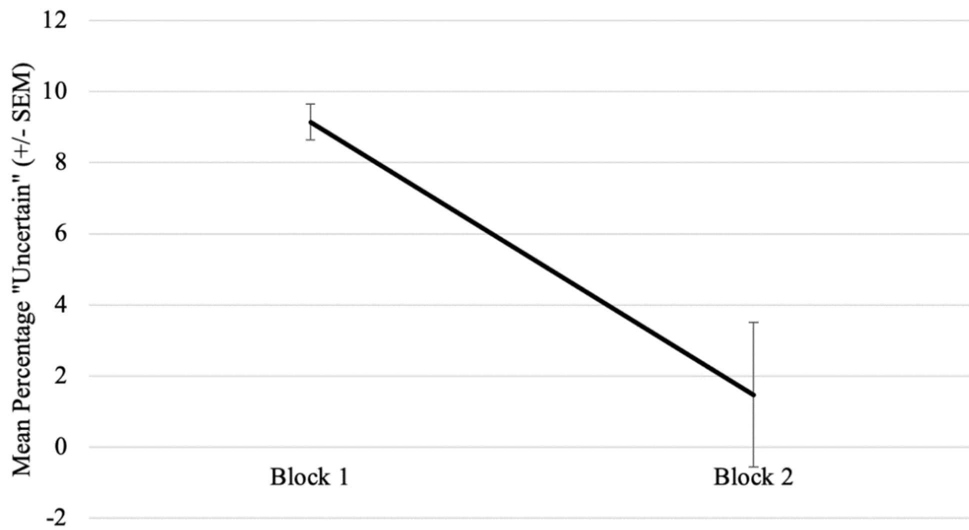


Figure 11. Average percentage of "Uncertain" responses during training for participants in the Uncertainty Monitoring condition.

Experiment 1 Discussion

The goal of Experiment 1 was to investigate the role of uncertainty monitoring in category learning and transfer. As predicted, learning and transfer was greater for those trained in the Uncertainty Monitoring condition. Participants were confident and generally able to accurately calibrate their perceived performance with their actual performance; however, this did not differ between the two training conditions as originally predicted. Although accurate calibration is typically thought of as an indicative of greater uncertainty monitoring, we cannot conclude that differences in task performance were due to differences in metacognition and uncertainty monitoring. One potential explanation for these results is differences in the type of feedback provided to the two training conditions. Participants in both conditions received verification feedback for categorical responses; however, participants in the uncertainty monitoring condition also received explanatory and elaborative feedback if they selected the “uncertain” response option. The explanatory and elaborative feedback consisted of the correct answer, and a brief caption elaborating on the answer. It is possible that some participants may have learned categorical rules and diagnostic features because of explanatory and elaborative feedback, instead of metacognitive processes. Experiment 2 addressed this concern and assessed the role of feedback on performance during uncertainty monitoring.

CHAPTER 3

EXPERIMENT 2A

Background

A potential limitation of Experiment 1 involves varying feedback types between the two training conditions. Feedback provides learners with information and opportunities to correct errors and deficiencies in knowledge which can differentially impact learning. Specifically, explanatory and elaborative (EE) feedback is thought to help students develop a deeper understanding of information relative to simple verification feedback (Butler et al., 2013; Fazio, Huelser, Johnson, & Marsh, 2010; Pashler, Cepeda, Wixted, & Rohrer, 2005). Although the results of Experiment 1 suggest that uncertainty monitoring training may be superior in supporting performance, it is possible that the observed advantages were due to access to EE feedback instead of uncertainty monitoring processes. Participants may have used the "uncertain" response option to gain feedback and adaptively complete the task, rather than use it to monitor their learning (Paul et al., 2011). Experiment 2 addressed the potential issue of feedback and investigated the methodological factors that impact performance.

The design of Experiment 2a was similar to Experiment 1 and utilized the same category learning tasks to train and test participants on Chemistry concepts. Experiment 2a assessed the impact of both verification and EE feedback on category learning and transfer across training conditions. It utilized a 2 training methodology (Uncertainty Monitoring vs. Forced Response) x 2 feedback type (Verification vs. Explanatory/Elaborative) between-subjects design. Experiment 2a aimed to replicate the advantage of uncertainty monitoring training and extend the findings from Experiment 1 to conditions in which feedback was matched across training methods.

If performance differences in Experiment 1 were solely due to differences in feedback type, then providing EE feedback across experimental conditions should eliminate those differences and performance should be enhanced for any participant who received EE feedback. However, if learning was supported by uncertainty monitoring training, then participants who are given the option to report uncertainty should perform better than participants who are not given the option, regardless of feedback type (see Figure 12). This was based upon prior research that suggested that EE feedback does not benefit learning any more than simple verification or correct answer feedback (Bangert-Drowns et al., 1991; Kulhavy et al., 1989; Smits et al., 2008)

	If performance differences observed in Experiment 1 were due to:		Predicted results for Experiment 2a under the same feedback conditions
Hypotheses	Differences in feedback type	→	No performance differences between training methods, only by feedback type (EE and verification feedback)
	Uncertainty monitoring training and access to an uncertain response option	→	General advantage of Uncertainty Monitoring training on performance

Figure 12. Hypotheses and predictions for Experiment 2a.

Method

Participants and Design

One-hundred and sixty-six undergraduate college students[4] ($N = 166$) from the University of Maine were recruited from the department of psychology's research pool to participate online via Qualtrics Survey. Participants received partial course credit for their participation and were randomly assigned to one of four experimental conditions in the 2 training methodology

[4] An $n = 30$ per condition was chosen based on the design and results from Experiment 1. Data collection continued beyond this target in order to provide participants with sufficient research opportunities.

(Uncertainty Monitoring vs. Forced Response) x 2 feedback type (Verification vs. EE) design. A total of 14 participants were excluded from analysis because they did not complete the experiment or were statistical outliers (i.e., more than 3 SD from the mean on average training accuracy, accuracy during the final block of training, or test phase); see Table 2.

Table 2. Number of participants in each of the conditions recruited from the University of Maine for Experiment 2a.

Training Condition	**Initial sample** $N = 166$	**Remaining sample** $N = 152$
Uncertainty Monitoring with Verification Feedback	41	38
Uncertainty Monitoring with Explanatory/Elaborative Feedback	40	34
Forced Response with Verification Feedback	43	43
Forced Response with Explanatory/Elaborative Feedback	42	37

Stimuli

The stimuli used in this experiment were the same stimuli used in Experiment 1. They consisted of different objects varying in pH levels and category membership (e.g., Acidic or Basic). All training stimuli were outlined by different colors that corresponded with the object's acidity and pH level. Category membership could be determined by the color of the outline of the training stimulus (e.g., Acidic = reds, yellows, and lighter shades of green; Basic = darker shades of green, blues, and purples). A novel set of stimuli were used during test phase to assess learning and transfer of categorical knowledge. All test stimuli retained the same rules and diagnostic features as those used in training but were visually different.

Procedure

All tasks and procedures were identical to Experiment 1. Participants were randomly assigned to one of the four experimental conditions (below) and instructed to complete 2 blocks of training and one block of test phase.

Uncertainty Monitoring training with Verification Feedback

During training phase, participants in this condition were shown a single stimulus on the center of the screen and were instructed to either sort it into one of two contrasting categories (e.g., Acidic or Basic) or respond with "uncertain". For consistency, the feedback approach in this condition mirrors that of Experiment 1. For example, if participants selected the Acidic or Basic category options, they received verification feedback (e.g., "CORRECT: Acidic" or "WRONG: Acidic"). If participants selected the "uncertain" option, they received explanatory and elaborative feedback, which consisted of the correct answer, and a caption elaborating on the answer (e.g., "This belongs in the Basic category because it has an approximate pH level of 13 and has a purple outline"). Participants were told that an incorrect answer would result in a 10 second "timeout" and delay the start of the next trial, whereas selecting the correct answer or "uncertain" option would allow them to proceed to the next trial; see Figure 13.

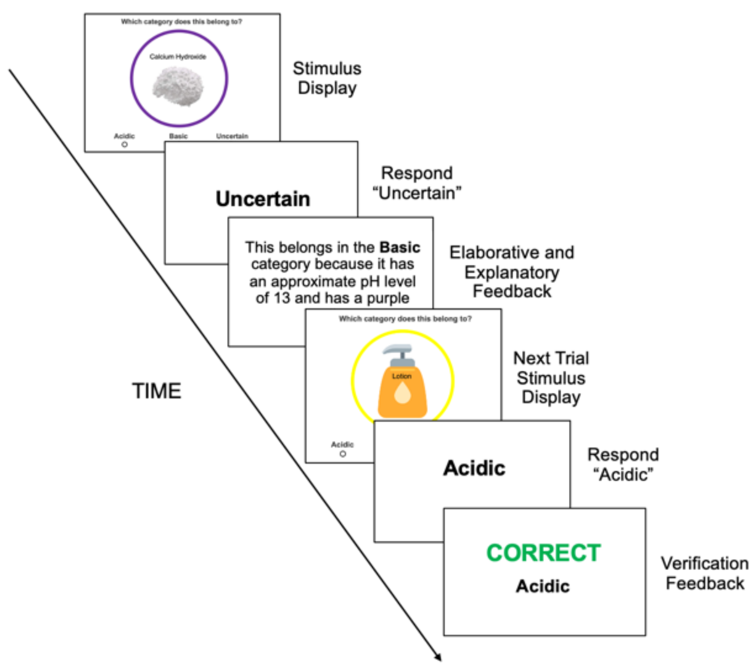


Figure 13. Example display for Uncertainty Monitoring with Verification Feedback condition.

Uncertainty Monitoring training with Explanatory and Elaborative Feedback

Participants in this condition were also shown a single stimulus on the screen and had the option to select one of two contrasting categories or respond with “uncertain”. Participants received explanatory and elaborative feedback for all their responses during training (e.g., “CORRECT: This belongs in the Basic category because it has an approximate pH level of 13 and has a purple outline” or “WRONG: This belongs in the Basic category because it has an approximate pH level of 13 and has a purple outline”). Participants were told that correct answers would allow them to proceed to the next trial, but incorrect answers will result in a 10 second “timeout” and delay the start of the next trial; see Figure 14.

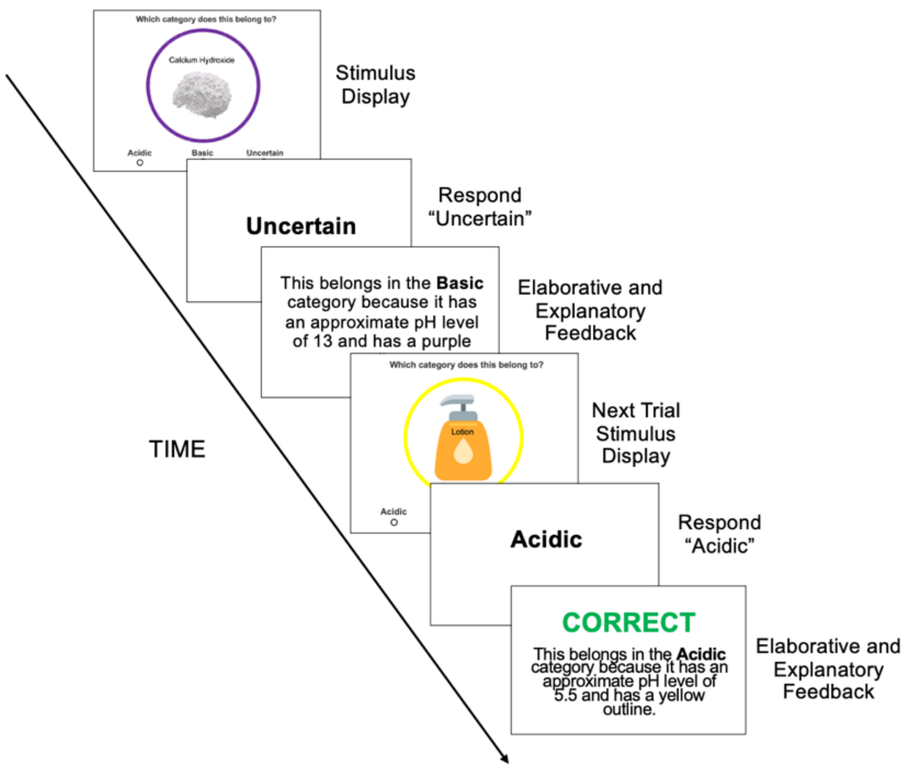


Figure 14. Example display for Uncertainty Monitoring condition with Explanatory and Elaborative Feedback.

Forced Response training with Verification Feedback

Unlike Uncertainty Monitoring training, participants in the *Forced Response* training conditions were not provided with an "uncertain" response option during training phase. Participants in the *Forced Response* training conditions were shown stimuli on the screen and instructed to sort them into one of two contrasting categories (e.g., Acidic or Basic). Participants in this condition received verification feedback (e.g., "CORRECT: Basic" or "WRONG: Basic") for their responses. Participants were told that correct answers allowed them to proceed to the next trial, but incorrect answers would result in a 10 second "timeout" and delay the start of the next trial; see Figure 15.

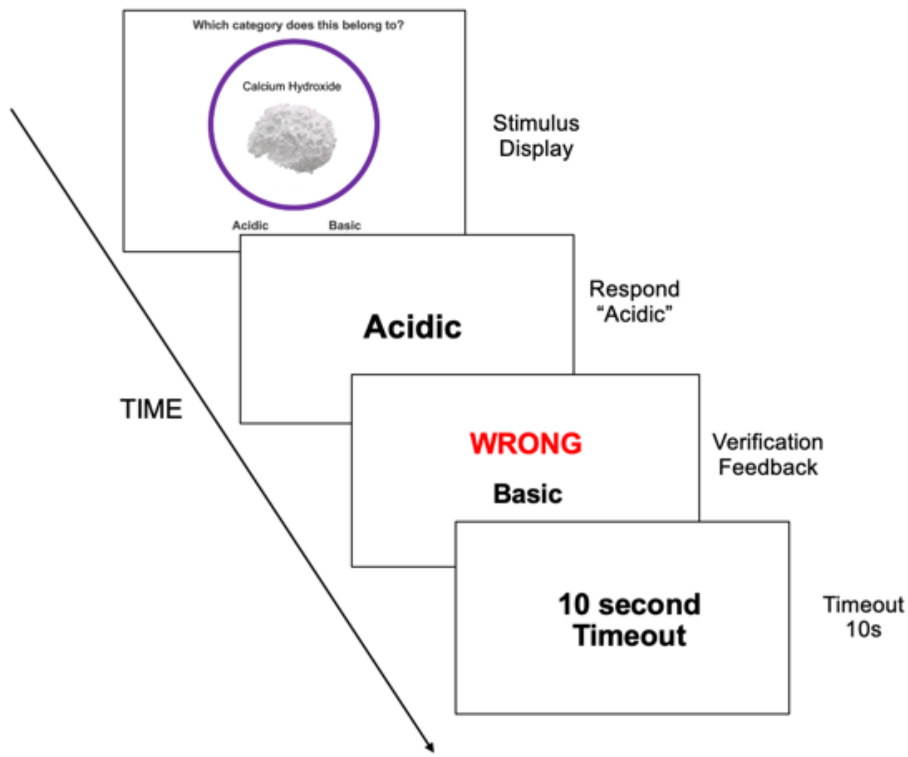


Figure 15. Example display for Forced Response condition with Verification Feedback.

Forced Response training with Explanatory and Elaborative Feedback

Participants in this condition were shown a single stimulus on the screen and sorted it into one of two contrasting categories (e.g., Acidic or Basic). Participants received explanatory and elaborative feedback for all their responses and were told that correct answers would allow them to proceed to the next trial, but incorrect answers would result in a 10 second "timeout" and delay the start of the next trial; see Figure 16.

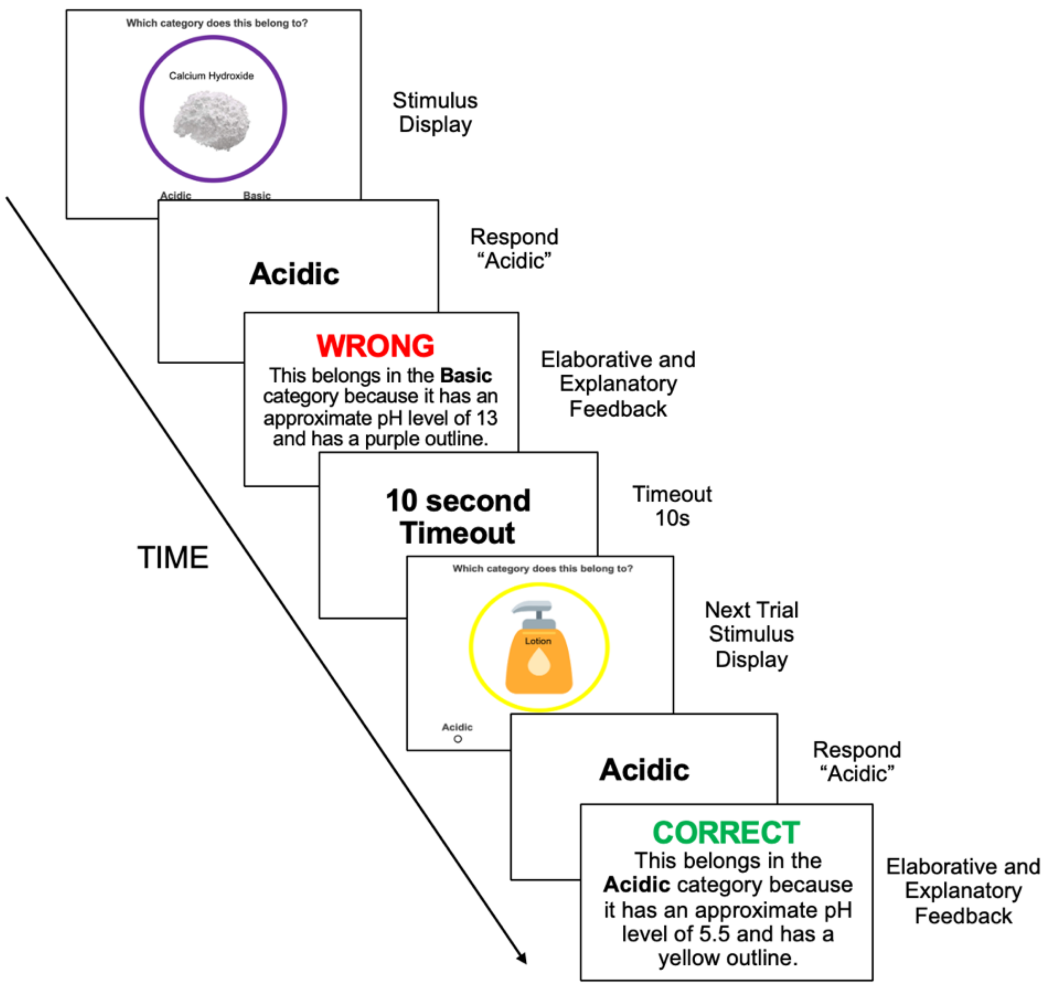


Figure 16. Example display for Forced Response condition with Explanatory and Elaborative Feedback.

Upon completion of the training phase, all participants were tested on a different task with a different set of stimuli. Test phase was used to assess participants' ability to transfer learned information to a novel context, where the task question and stimuli appeared different, but the demands of the tasks were the same (see Figure 5). After every test trial, participants reported their confidence in their test responses and were not provided any feedback nor option to report uncertainty. After the test phase, all participants completed a brief post-task questionnaire which included questions that probed participants' attentiveness, decision-making strategies, confidence, and general knowledge of the information learned (see Appendix B).

Data Analysis Procedure

To assess whether performance was influenced by training method and dependent on feedback type, a three-way ANOVA was conducted to examine the effect of training method (Uncertainty Monitoring vs. Forced Response), feedback type (Verification vs. EE) and time (Block 1 vs. Block 2) on learning during training phase. Separate two-way ANOVAs were conducted to further investigate the impact of training method (Uncertainty Monitoring vs. Forced Response) and feedback type (Verification vs. EE) on participants' confidence and transfer performance during test phase.

It was predicted that if performance was solely dependent on feedback type, then there would only be observable differences in accuracy and confidence between the two feedback conditions, but not between training methods. However, if performance depends on uncertainty monitoring training, then enhancements should still be observed, even when feedback is matched across training conditions. Planned contrasts were used to assess task performance across feedback conditions, and compared the Uncertainty Monitoring EE feedback condition with the other three experimental conditions.

Results

Training Phase: Task Performance

Inspection of data suggests that performance generally improved throughout training for all participants (see Figure 17). A three-way, mixed model ANOVA, with training (uncertainty monitoring vs. forced response), feedback (verification vs. EE) and time (block 1 vs. block 2), showed a significant main effect of training method [$F(1, 148) = 21.84$, $p < .001$, $\eta p^2 = .129$], feedback type [$F(1, 148) = 44.51$, $p < .001$, $\eta p^2 = .231$], and time [$F(1, 148) = 259.35$, $p < .001$, $\eta p^2 = .637$] on training accuracy. There was no significant interaction [$F(1, 148) = 3.195$, $p = .076$, $\eta p^2 = .021$]. These data suggest that performance improved over time for all conditions, with an overall benefit of EE feedback.

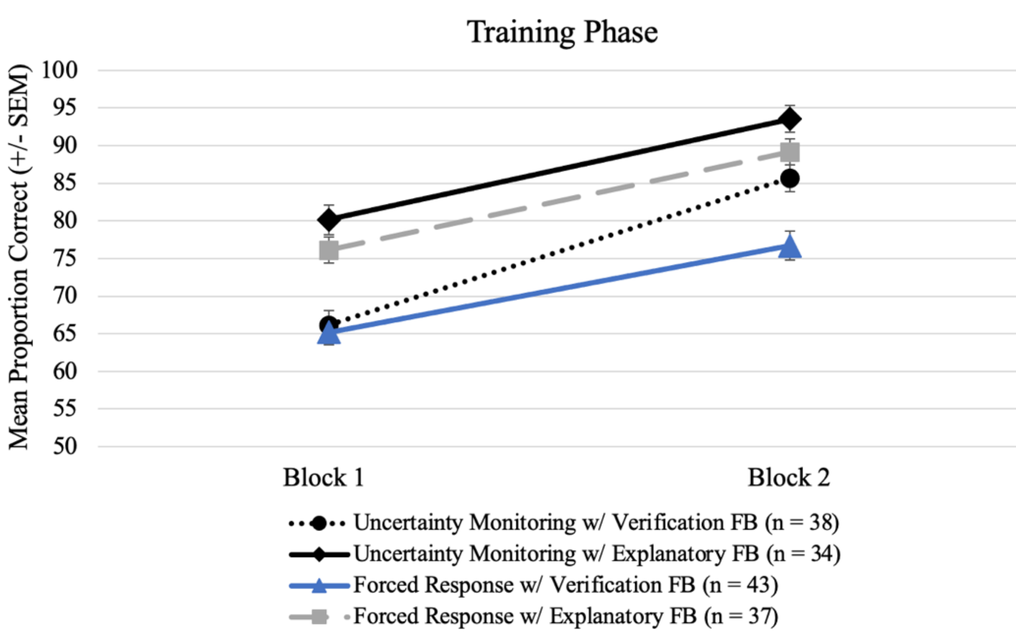


Figure 17. Performance for four training conditions during training phase.

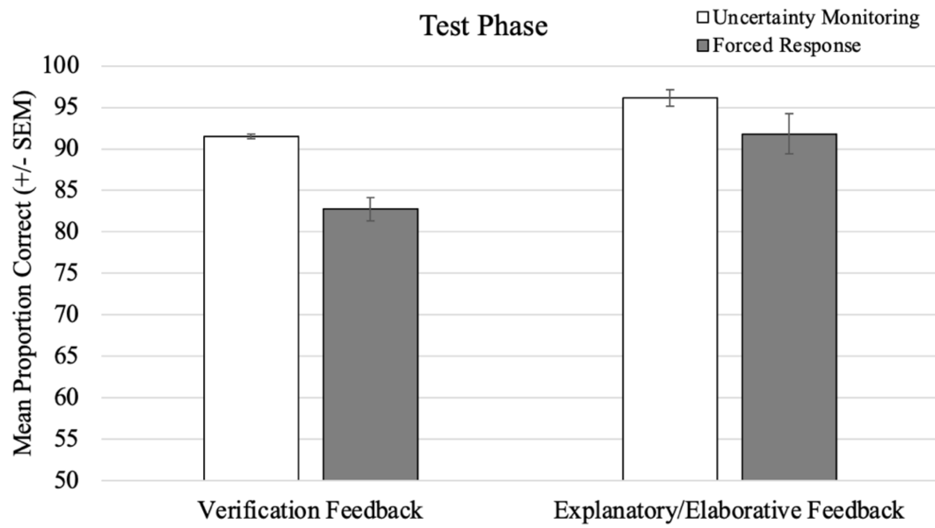
Test Phase: Task Performance

Inspection of the test phase data suggest that participants were generally able to transfer knowledge to a novel task with performance varying by training method and feedback type (see Figure 18, top). This observation was supported by a 2 training (uncertainty monitoring vs. forced response) x 2 feedback (verification vs. EE) ANOVA[5], which revealed a significant main effect of training method [$F(1, 148) = 15.94$, $p < .001$, $\eta p^2 = .10$] and feedback type [$F(1, 148) = 17.489$ $p < .001$, $\eta p^2 = .106$] on test performance. Specifically, an *a priori* planned contrast comparing the uncertainty monitoring EE feedback condition with the other three conditions suggest an advantage of combining such a training method with such feedback to support test accuracy [$F(1, 148) = 14.48$, $p < .001$, $\eta p^2 = .09$]; see Figure 18.

Further inspection of test phase data suggests that the ability to estimate pH levels of test stimuli varied by training method, as participants trained with uncertainty monitoring appeared to be more accurate in estimating pH (see Figure 18, bottom). A two-way ANOVA with training (uncertainty monitoring vs. forced response) and feedback (EE vs. verification), revealed a significant main effect of training method [$F(1, 145) = 8.726$, $p = .004$, $\eta p^2 = .057$] on pH accuracy, but there was no main effect of feedback [$F(1, 145) = 1.445$, $p = .231$, $\eta p^2 = .010$] and the interaction was not significant [$F(1, 145) = .037$, $p = .848$, $\eta p^2 = .00$]. This suggests that

[5] Levene's test indicated unequal variances ($p < .001$). Subsequent analyses were conducted using ANOVAs, which are robust against violations of homogeneity of variance, therefore, no corrections were made. In addition, a non-parametric Kruskal-Wallis test was also conducted to examine group differences and found that test accuracy significantly differed between the four conditions (x^2 (3) = 12.331, $p < .001$). Pairwise comparison using a Mann-Whitney Test with Bonferroni corrections suggests that when participants are given explanatory and elaborative feedback, those who are trained to monitor their uncertainty ($M_{rank} = 42.07$) outperform participants who are required to simply make a categorial response ($M_{rank} = 30.42$); $p = .012$.

while participants were generally able to transfer knowledge from training to test phase, the extent to which participants can transfer knowledge may depend on training method.



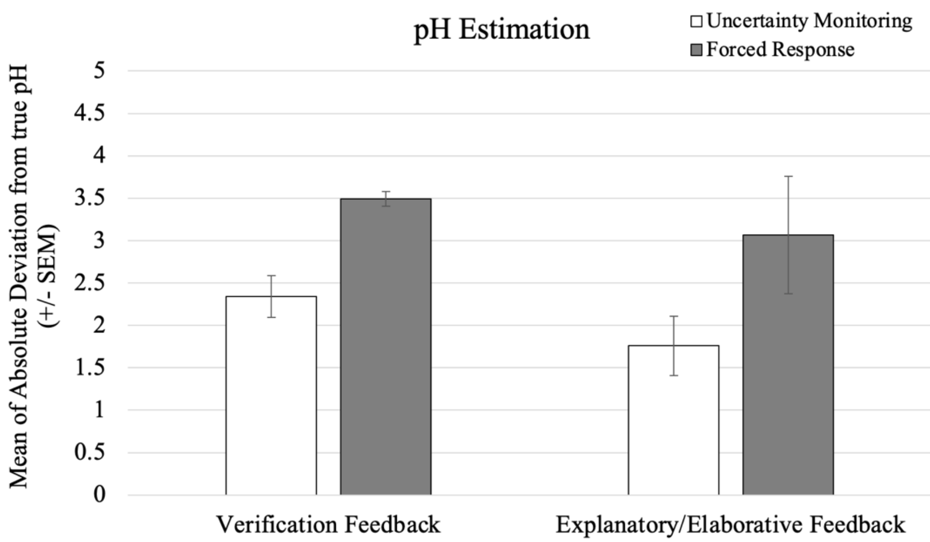


Figure 18. Performance for four training conditions during test phase on: (Top) Category Accuracy, (Bottom) Estimating pH levels of test stimuli (Average error per trial was computed by taking the absolute deviation from the true pH value; lower scores indicate better accuracy).

Test Phase: Confidence

Additional analysis using simple linear regression suggest that confidence during test phase was a predictive of performance for some participants[6], as it accounted for a significant proportion of test accuracy in the Uncertainty Monitoring with Verification feedback condition [R^2 = .161, F(1, 36) = 6.902, p = .013], and Forced Response with Verification feedback condition [R^2 = .195, F(1, 37) = 8.987, p = .005]; see Table 3 and Figure 19. Contrary to hypotheses, *a priori* planned comparisons suggested that confidence for participants in the uncertainty monitoring EE feedback condition was only significantly different from those in the forced response verification feedback condition (p < .001), and not other groups (p's > .49). Lowest confidence was observed for participants in the forced response verification feedback condition (p's < .012); see Figure 20.

A two-way ANOVA[7] was conducted to further examine the effect of training method (uncertainty monitoring vs. forced response) and feedback type (verification vs. EE) on confidence during test phase. Results show a significant main effect of training [F(1, 148) = 10.61, p = .001, ηp^2 = .07] and feedback [F(1, 148) = 20.83 p < .001, ηp^2 = .123] on test confidence. The interaction was not significant [F(3, 148) = 1.23, p = .269, ηp^2 = .01].

[6] Four participants in the Forced Response Verification feedback condition had standardized residual scores of +/- 3. These participants were excluded from analyses.

[7] Levene's test indicated unequal variances (p < .001). Subsequent analyses were conducted using ANOVAs, which are robust against violations of homogeneity of variance, therefore, no corrections were made. In addition, a non-parametric Kruskal-Wallis test was conducted to examine group differences and found that response confidence during test phase significantly differed between the four conditions (x^2 (3) = 23.675, p < .001). Pairwise comparisons using Mann-Whitney Tests and Bonferroni corrections suggested that confidence was higher for participants in the uncertainty monitoring training condition who received EE feedback (M_{rank} = 42.85) compared to verification feedback (M_{rank} = 30.82); p = .015. Likewise, participants in the forced response training condition who received EE feedback also reported greater response confidence (M_{rank} = 49.81) compared to those who received verification feedback (M_{rank} = 32.49); p = .001. However, no significant differences in confidence were observed across training methods (p's > .072).

Table 3. Regression Analysis summary for confidence predicting test accuracy in Experiment 2a.

		Unstandardized Coefficients		Standardized Coefficients		
Training condition	***df***	**B**	***SE***	**β**	***t***	***p***
Uncertainty Monitoring with Verification Feedback	36	1.741	0.663	0.401	2.627	0.013
Uncertainty Monitoring with Explanatory/Elaborative Feedback	32	0.125	0.298	0.074	0.419	0.678
Forced Response with Verification Feedback	37	2.295	0.765	0.442	2.998	0.005
Forced Response with Explanatory/Elaborative Feedback	35	2.255	1.246	0.292	1.809	0.079

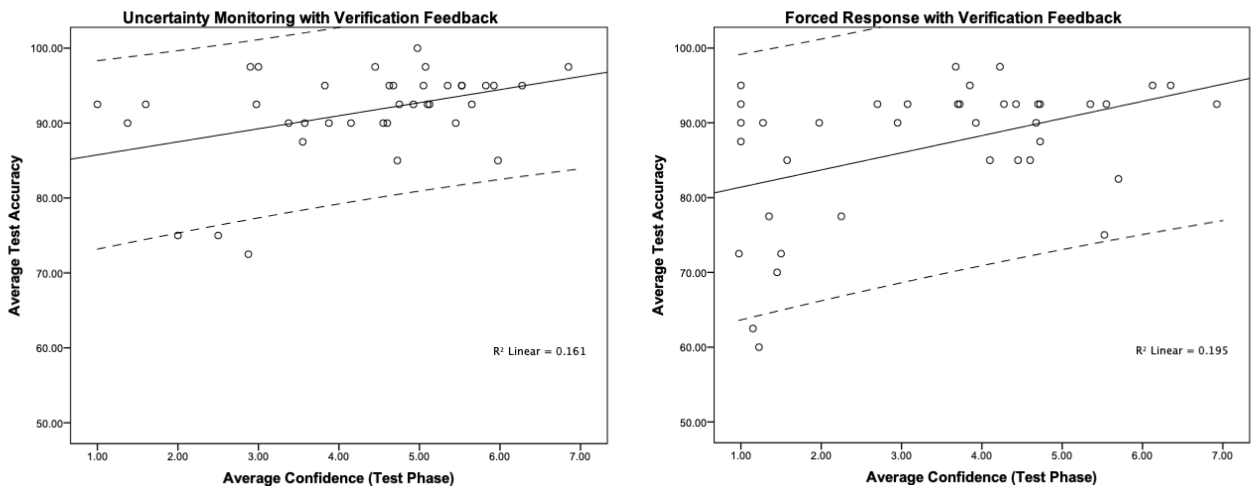


Figure 19. Average test accuracy by confidence for (Left) Uncertainty Monitoring with Verification Feedback, and (Right) Forced Response with Verification feedback condition.

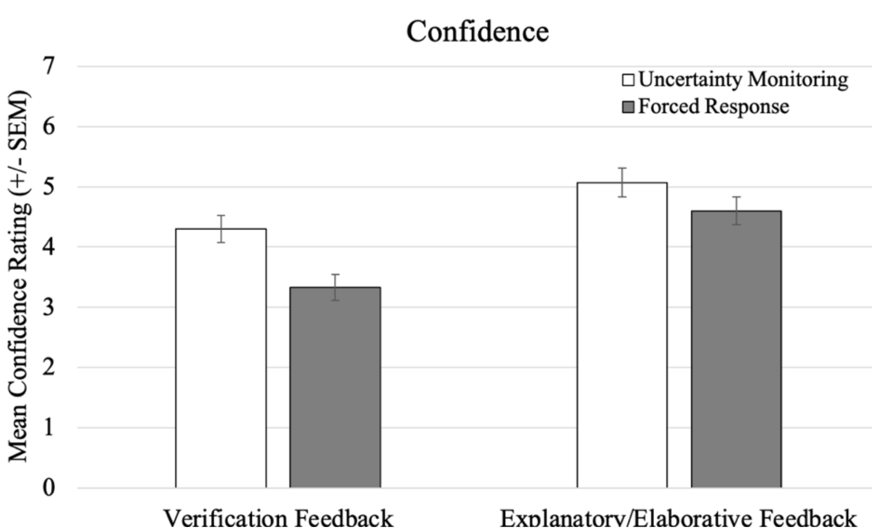


Figure 20. Average confidence during test phase by training and feedback.

Uncertainty Monitoring Training

A primary question in Experiment 2a was the role of uncertainty monitoring on performance, and the utility of the uncertain response option following changes to feedback type. As seen in Figure 20, participants in the uncertainty monitoring condition who received verification feedback utilized the “uncertain” response option more than those who were provided with EE feedback. This suggests that feedback type may impact uncertainty responding, as more detailed EE feedback may reduce uncertainty early in training and increase the rate of learning. Paired samples t-tests show that significant decreases in “uncertain” responding from block 1 to block 2 was evident for both EE [$t(33) = 2.68$, $p = .011$, $g = .547$] and verification feedback conditions [$t(37) = 3.93$, $p < .001$, $g = .715$]; see Figure 21.

Taken altogether, these results suggest that both training method and feedback type can impact performance, with performance being greater for those trained with a combination of Uncertainty Monitoring and EE feedback.

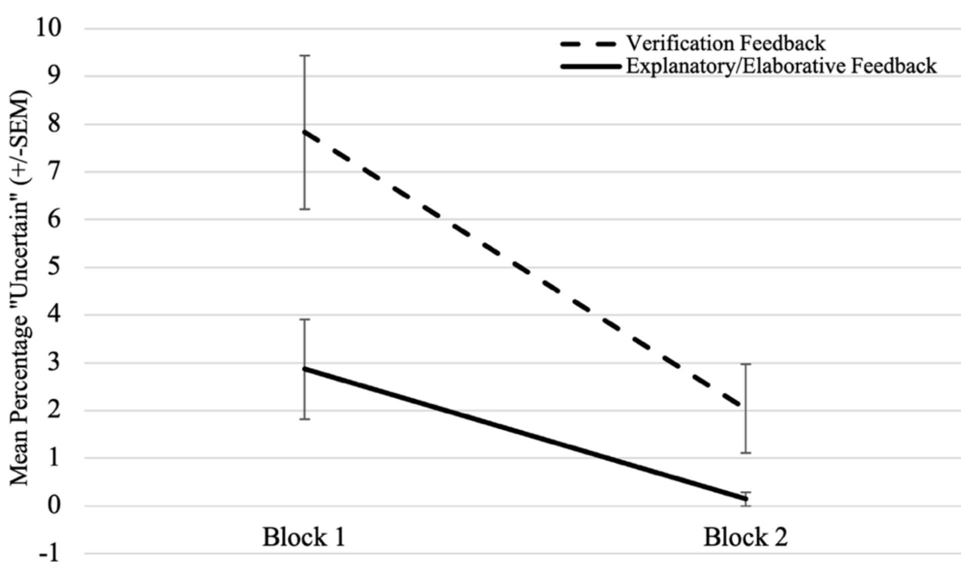


Figure 21. Average percentage of “Uncertain” responses between feedback conditions within the Uncertainty Monitoring training condition.

Experiment 2a Discussion

The goal of Experiment 2a was to address the issue of feedback type in Experiment 1 and examine whether uncertainty monitoring training could support learning across different feedback conditions. The results suggest that participants who were trained with uncertainty monitoring outperformed participants who were simply required to make a categorial response, even when feedback was matched. Based on the data, EE feedback was superior in supporting learning across training conditions compared to verification feedback. This may lend some support to the notion that feedback may have contributed to the performance differences observed in Experiment 1. The present data, however, demonstrates a general benefit of uncertainty monitoring training on category learning and transfer.

One concern is that in Experiments 1 and 2a, participants' confidence ratings were similar across training conditions, despite an advantage of uncertainty monitoring training. The only difference in confidence appeared to be due to feedback type, as confidence was higher for participants who received EE feedback. A potential explanation for this is that confidence was assessed post-training, during test phase. Given that test performance required the same categorical knowledge used during training, participants likely felt confident in their test responses after successfully learning the categories in the training phase. Another explanation is that metacognitive skills and processes, such as uncertainty monitoring, have been shown to increase confidence and judgment of performance. It is possible that participants in the forced response training conditions were also monitoring their performance and were comparably confident in their test responses. A limitation of Experiments 1 and 2a, however, is that they did not gauge whether participants in the forced response training conditions were monitoring their learning and uncertainty.

In sum, these data suggest that regardless of training method, EE feedback is superior in supporting learning and transfer compared to verification feedback. Best performance, however, was observed in participants who were trained to monitor their uncertainty and simultaneously received EE feedback.

CHAPTER 3

EXPERIMENT 2B

Background

The results from Experiment 2a mirrored those from Experiment 1, which suggest an advantage of uncertainty monitoring training on performance. However, there was evidence that learning depended upon feedback type as well. Experiment 2b of this dissertation further investigated the role of feedback by removing feedback entirely during training. It was predicted that if performance differences were solely dependent upon feedback, then removing feedback should eliminate those differences and performance should be similar across training conditions. However, if there is a benefit of uncertainty monitoring training, then participants who have access to an uncertain response option should outperform those who did not.

A limitation in Experiments 1 and 2a was that confidence was assessed post-training during test phase, after learning was complete and confidence was reasonably higher. Examining confidence during test phase does not provide an accurate measure of metacognition nor demonstrate the differences between training methods. In addition, Experiments 1 and 2a did not gauge whether participants in the forced response conditions were also monitoring their learning, despite not having an option to report uncertainty. Experiment 2b addressed these limitations and included additional measures of metacognition to assess participants' ability to judge their own performance, and compared it to their actual performance (e.g., calibration accuracy). Experiment 2b also implemented trial-by-trial confidence ratings during training phase, which has been shown to induce performance monitoring and was used as another measure of metacognition (Balakrishnan & Ratcliff, 1996).

Experiment 2b further addressed the issue of feedback by including two experimental conditions in which participants were not shown feedback. Experiment 2b reran the four experimental conditions from Experiment 2a but utilized a 2 training methodology (Uncertainty Monitoring vs. Forced Response) x 3 feedback type (Verification, EE, no feedback) design under revised procedures. Experiment 2b aimed to replicate the overall benefit of uncertainty monitoring training on performance and assessed metacognition across conditions.

Based on the results from Experiments 1 and 2a, it was predicted that there would be a benefit of uncertainty monitoring training on learning and transfer, regardless of whether participants received EE or verification feedback. However, if learning was dependent upon feedback, then performance would not differ between training methods when feedback is matched across conditions (see Figure 22).

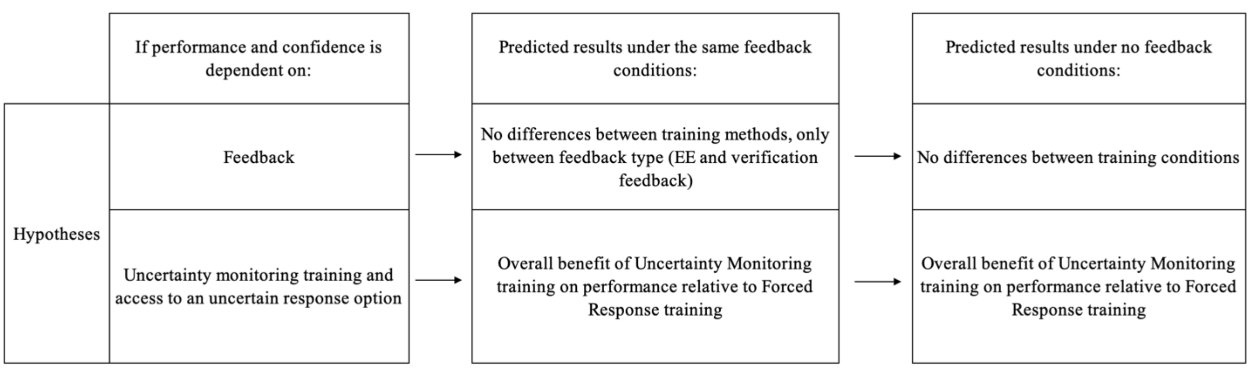


Figure 22. Hypotheses and predictions for Experiment 2b.

Method

Participants

One-hundred and ninety-eight undergraduate college students[8] ($N = 198$) from the University of Maine were recruited from the department of psychology's research pool to participate online via Qualtrics Survey. Participants received partial course credit for their participation. Participants were randomly assigned to one of six experimental conditions in the 2 training methodology (Uncertainty Monitoring vs. Forced Response) x 3 feedback type (Verification, EE, No feedback) design. A total of 16 participants were excluded from analysis because they did not complete the experiment or were statistical outliers (i.e., more than 3 SD from the mean on average training accuracy, accuracy during the final block of training, or test phase); see Table 4.

Table 4. Number of participants in each of the conditions recruited from the University of Maine for Experiment 2b.

Training Condition	**Initial sample** $N = 198$	**Remaining sample** $N = 182$
Uncertainty Monitoring with Verification Feedback	31	31
Uncertainty Monitoring with Explanatory/Elaborative Feedback	34	30
Forced Response with Verification Feedback	35	31
Forced Response with Explanatory/Elaborative Feedback	33	31
Uncertainty Monitoring with No Feedback	33	28
Forced Response with No Feedback	32	31

Stimuli

The stimuli were the same as those used in Experiments 1 and 2a.

[8] An $n = 30$ per condition was chosen based on the design and results from Experiments 1 and 2a.

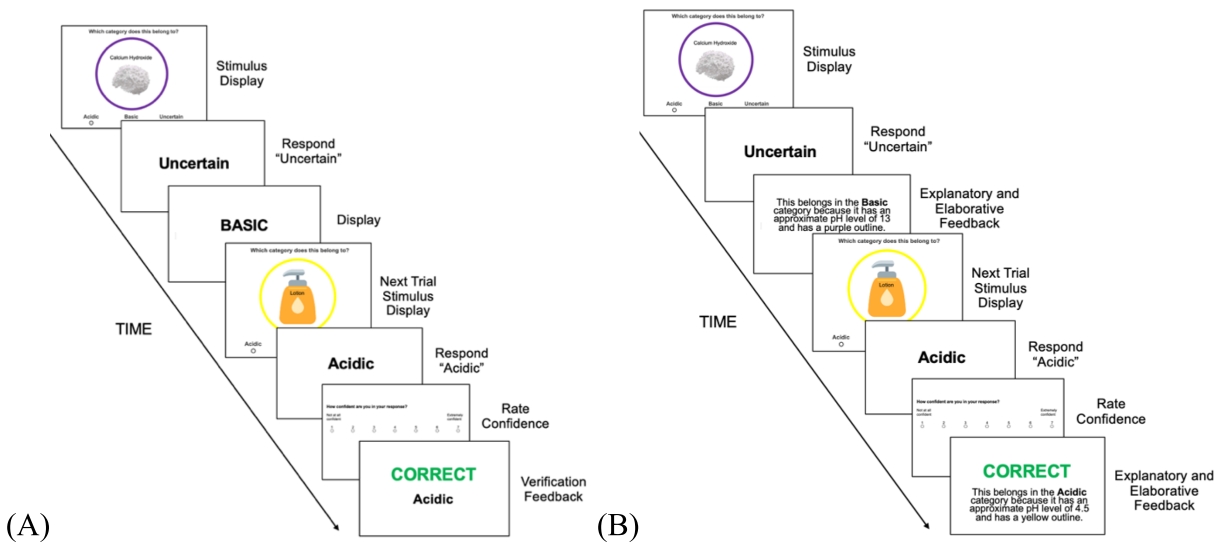
Procedure

The procedure for Experiment 2b was similar to Experiment 2a; however, participants were randomly assigned to one of the six experimental conditions (below), two of which did not provide any feedback. Participants were also instructed to complete trial-by-trial confidence ratings during training phase (see Figure 23).

1. Uncertainty Monitoring training with Verification Feedback
2. Uncertainty Monitoring training with Explanatory and Elaborative Feedback
3. Forced Response training with Verification Feedback
4. Forced Response training with Explanatory and Elaborative Feedback
5. Uncertainty Monitoring training with No Feedback
6. Forced Response training with No Feedback

During training, all participants were shown a single stimulus in the center of the screen and were instructed to sort it into one of two contrasting categories (e.g., Acidic or Basic). Participants in Uncertainty Monitoring training had the additional option to respond with "uncertain", whereas participants in Forced Response training did not. After each trial, participants were prompted to report their confidence in their categorical responses on a Likert-type scale ranging from 1 (Not at all Confident) to 7 (Extremely Confident). Depending on their assigned feedback condition, participants received either verification feedback (e.g., "CORRECT: Basic" or "WRONG: Basic"), explanatory and elaborative feedback (e.g., "This belongs in the Basic category because it has an approximate pH level of 13 and has a purple outline"), or no feedback following their confidence ratings. Participants who received feedback were told that an incorrect answer would result in a 10 second "timeout", whereas correct or "uncertain" responses allowed them to proceed to the next trial (see Figure 23).

After the training phase, all participants were tested on the same task and stimuli used in Experiments 1 and 2a. At the end of test phase, all participants completed a brief post-task questionnaire that probed participants' decision-making strategies, attention, and general knowledge about the information learned. The post-task questionnaire also gauged participants' confidence and perceived task performance on a 100-point scale (see Appendix B).



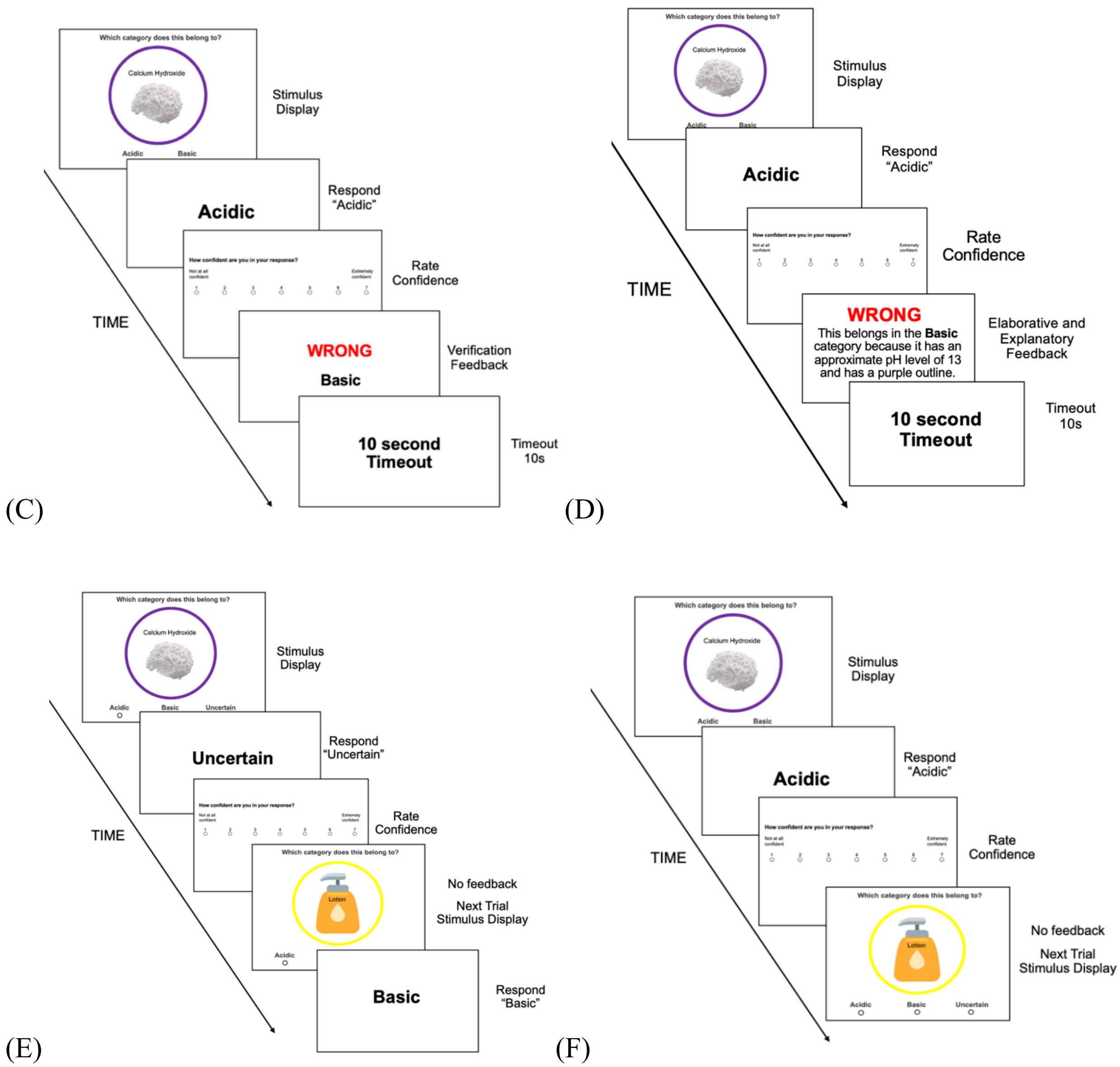


Figure 23. Example displays for six training conditions in Experiment 2b: (A) Uncertainty Monitoring training with Verification Feedback, (B) Uncertainty Monitoring training with Explanatory/Elaborative Feedback, (C) Forced Response training with Verification Feedback, (D) Forced Response training with Explanatory/Elaborative Feedback, (E) Uncertainty Monitoring training with No Feedback, (F) Forced Response training with No Feedback.

Data Analysis Procedure

The data was analyzed in the same way as Experiments 1 and 2a. Average performance across training blocks were calculated to examine accuracy and learning curves. Separate three-way, mixed model ANOVAs were conducted to examine the effect of training method (Uncertainty Monitoring vs. Forced Response), feedback type (Verification, EE, no feedback), and time (Block 1 vs. Block 2) on learning and confidence throughout training phase.

Additionally, two-way ANOVAs were conducted to further investigate the impact of training and feedback on test performance and calibration accuracy. Calibration between participants' perceived performance and actual performance was used as an additional measure of metacognition. Calibration accuracy was computed by taking the difference between participants' self-reported, perceived performance and their actual performance. Lower scores, closer to zero, indicated better judgment of performance and greater metacognition. Miscalibration was expected during initial stages of learning, but confidence and calibration were predicted to improve with learning for all conditions. Specifically, participants who monitored their uncertainty were expected to have higher confidence and greater calibration accuracy as uncertainty monitoring training has been shown to improve judgments of performance.

Based on the results from Experiment 2a, it was predicted that there would be a general benefit of EE feedback. However, overall performance was greater for uncertainty monitoring training. Thus, it was predicted that task accuracy, confidence, and calibration would depend on a combination of training and feedback. Specifically, planned contrasts were used to compare the Uncertainty Monitoring EE feedback condition with the other five experimental conditions

Results

Training Phase: Task Performance

Learning was evident for all conditions except those who did not receive feedback during training phase (see Figure 24). A three-way, mixed model ANOVA, with training (uncertainty monitoring vs. forced response), feedback (verification, EE, no feedback) and time (block 1 vs. block 2), showed a significant main effect of feedback type [$F(2, 176) = 49.11$, $p < .001$, $\eta p^2 = .358$] and time [$F(1, 176) = 352.54$, $p < .001$, $\eta p^2 = .667$] on performance during training phase, but no main effect of training method [$F(1, 176) = .652$, $p = .421$, $\eta p^2 = .004$]. The main effects were qualified by a significant interaction between training, feedback, and time [$F(2, 176) = 8.075$, $p < .001$, $\eta p^2 = .084$].

Further analyses revealed a simple main effect of feedback type on training accuracy for the uncertainty monitoring [Block 1: $F(2, 86) = 7.567$, $p = .001$, $\eta p^2 = .15$; Block 2: $F(2, 86) = 38.123$, $p < .001$, $\eta p^2 = .47$] and forced response conditions [Block 1: $F(2, 90) = 23.21$, $p < .001$, $\eta p^2 = .34$; Block 2: $F(2, 90) = 40.378$, $p < .001$, $\eta p^2 = .473$]. Pairwise comparisons using Sidak corrections indicated that performance for both training methods were significantly higher in block 1, when participants received EE feedback compared to other types of feedback (p's < .05). However, in block 2, performance for those who received EE feedback only differed from participants who did not receive feedback (p's < .001) but did not differ from those who received verification feedback (p's > .278) Furthermore, participants who did not receive feedback at all during training performed the worse in block 1 and block 2 (p's < .001).

These results were not surprising as feedback plays a role in learning, and learning was only evident in training conditions that provided feedback. In sum, these data suggest that performance for those who received either EE or verification feedback generally improved throughout training, with superior performance in EE feedback conditions, and inferior performance in no feedback conditions.

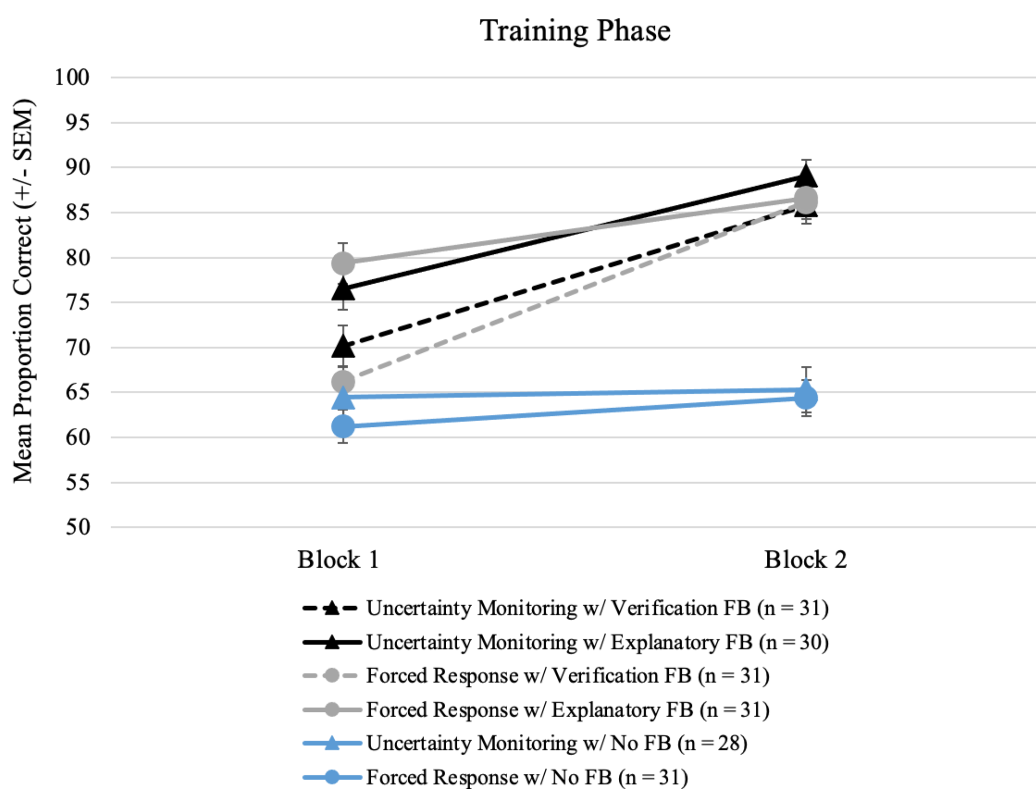


Figure 24. Performance for six training conditions during training phase on category accuracy.

Training Phase: Confidence

Recall that unlike Experiments 1 and 2a, Experiment 2b implemented trial-by-trial confidence ratings during training phase and served as an additional measure of metacognition. Confidence ratings were averaged for each block of training. Based on the results from Experiments 1 and 2a, it was expected that average confidence would increase with training but would not differ between groups that received either verification or EE feedback. These predictions were partly supported as a three-way, mixed model ANOVA, with training (uncertainty monitoring vs. forced response), feedback (verification, EE, no feedback) and time (block 1 vs. block 2), revealed a significant main effect of time [$F(1, 164) = 21.24$, $p < .001$, $\eta p^2 = .115$] and feedback type [$F(2, 164) = 13.69$, $p < .001$, $\eta p^2 = .143$] on confidence during training phase. However, there was no main effect of training method [$F(1, 164) = .009$, $p = .924$, $\eta p^2 = .000$] and the interaction between training method, feedback type, and time was not significant [$F(2, 164) = 1.546$, $p = .216$, $\eta p^2 = .019$]. These data suggests that confidence may vary by feedback type and amount of training (see Figure 25).

Additional analyses show that confidence was a predictor of performance, as it accounted for a significant proportion of training accuracy (see Table 5) for the following conditions[9]: Uncertainty Monitoring with EE feedback [$R^2 = .326$, $F(1, 24) = 11.616$, $p = .002$], Forced Response with EE feedback [$R^2 = .131$, $F(1, 29) = 4.361$, $p = .046$], and Uncertainty Monitoring with No Feedback [$R^2 = .187$, $F(1, 26) = 5.981$, $p = .022$]; see Figure 26.

Table 5. Regression Analysis summary for confidence predicting performance during training and test phase in Experiment 2b.

			Unstandardized Coefficients		**Standardized Coefficients**		
	Training condition	***df***	**B**	***SE***	**β**	***t***	***p***
Training Phase	Uncertainty Monitoring with Verification Feedback	24	2.129	1.852	0.228	1.149	0.262
	Uncertainty Monitoring with Explanatory/Elaborative Feedback	24	5.685	1.668	0.571	3.408	0.002
	Forced Response with Verification Feedback	27	1.493	1.993	0.143	0.749	0.46
	Forced Response with Explanatory/Elaborative Feedback	29	3.969	1.9	0.362	2.088	0.046
	Uncertainty Monitoring with No Feedback	26	5.203	2.127	0.432	2.446	0.022
	Forced Response with No Feedback	28	2.345	1.435	0.295	1.635	0.113
Test Phase	Uncertainty Monitoring with Verification Feedback	29	3.047	1.293	0.401	2.357	0.025
	Uncertainty Monitoring with Explanatory/Elaborative Feedback	28	1.888	0.73	0.439	2.587	0.015
	Forced Response with Verification Feedback	29	2.01	1.307	0.275	1.538	0.135
	Forced Response with Explanatory/Elaborative Feedback	29	0.418	1.329	0.058	0.315	0.755
	Uncertainty Monitoring with No Feedback	26	1.453	1.608	0.174	0.903	0.375
	Forced Response with No Feedback	29	-0.636	1.246	-0.094	-0.51	0.614

[9] Three participants in the Forced Response No Feedback condition, one participant in the Forced Response Explanatory Feedback condition, and one participant in the Forced Response Verification Feedback condition had standardized residual scores of +/- 3. These participants were excluded from analyses.

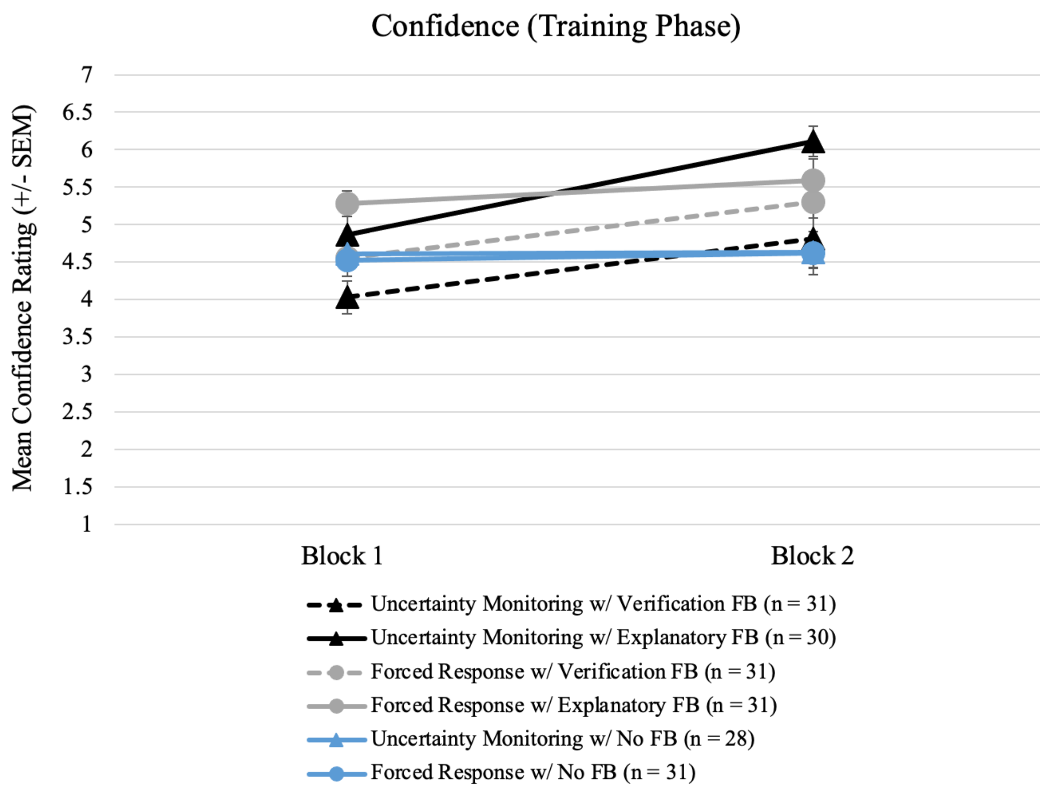
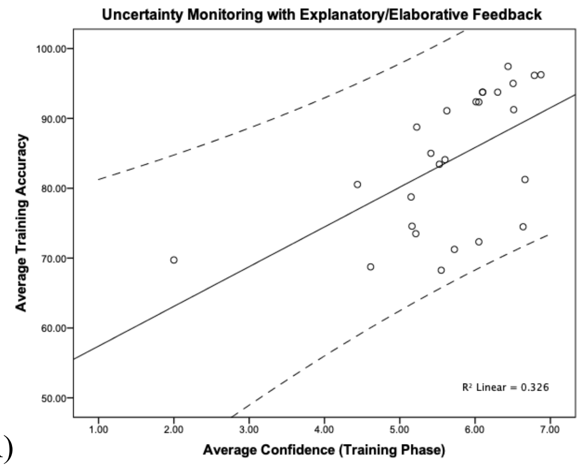
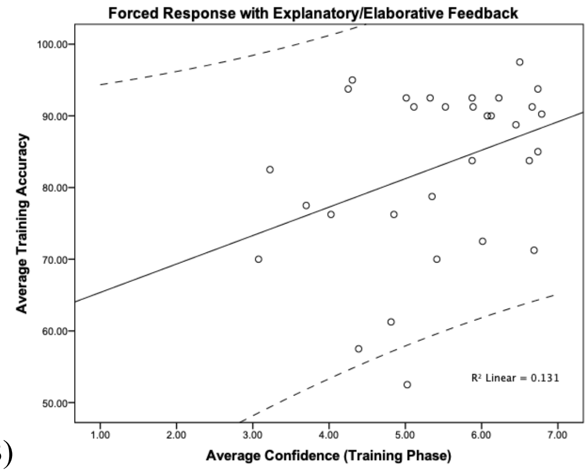


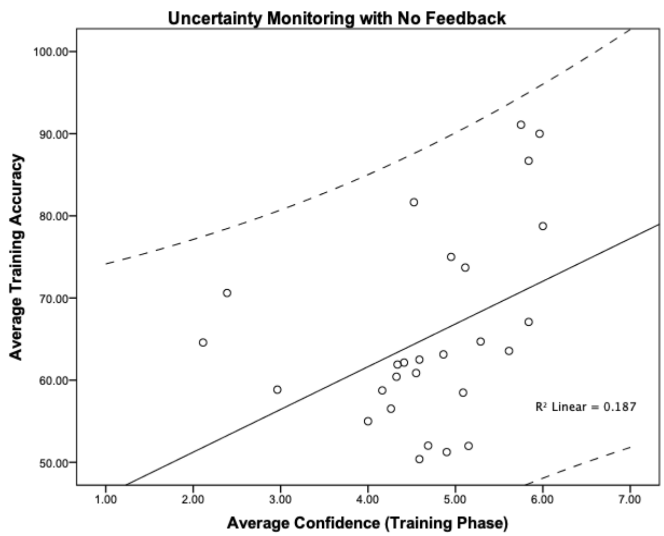
Figure 25. Average confidence ratings during training phase.



(A)



(B)



(C)

Figure 26. Average training accuracy by average confidence between (A) Uncertainty Monitoring with Explanatory/Elaborative Feedback, (B) Forced Response with Explanatory/Elaborative Feedback, and (C) Uncertainty Monitoring with No Feedback conditions. Dashed lines represent 95% confidence interval bands.

Training Phase: Calibration Accuracy

Prior research shows that monitoring uncertainty can improve confidence and judgment of performance. It was predicted that calibration between perceived performance and actual performance would be greater for participants who were trained with uncertainty monitoring. A two-way ANOVA, with training methodology (uncertainty monitoring vs. forced response) and feedback type (verification, EE, no feedback), revealed a main effect of feedback on calibration accuracy [$F(2, 176) = 7.044$, $p = .001$, $\eta p^2 = .074$], but no effect of training method [$F(1, 176) = 2.289$, $p = .132$, $\eta p^2 = .013$]. The interaction was not significant [$F(2, 176) = .056$, $p = .946$, $\eta p^2 = .001$]. *A priori* planned comparisons, however, indicated that participants trained on uncertainty monitoring with EE feedback were better able to judge their performance compared to other groups [$F(1, 176) = 6.415$, $p = .012$, $\eta p^2 = .04$]; see Figure 27. Taken altogether, these data suggest that the ability to assess learning and performance depends on feedback. However, at later stages of learning, calibration accuracy may depend on both training method and feedback type (see test phase results below).

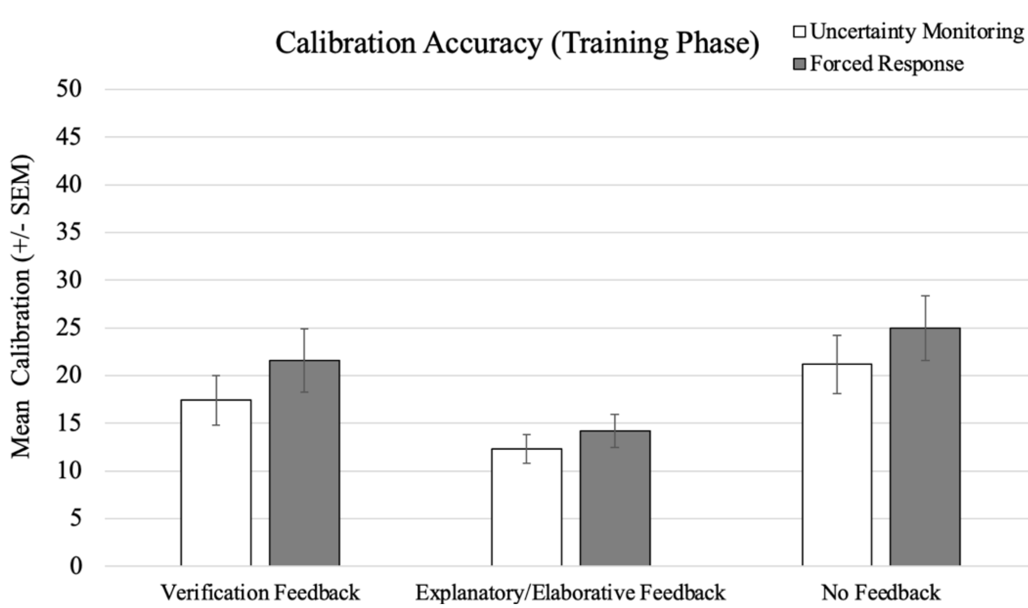


Figure 27. Average calibration accuracy between training methods by feedback type. Calibration accuracy was computed by taking the difference between participants' judgments of performance and their actual performance (lower scores closer to zero indicate greater calibration accuracy).

Test Phase: Task Performance

Inspection of the test phase data suggest that participants are generally able to transfer knowledge to novel tasks, with an advantage for those trained on uncertainty monitoring (see Figure 28). This observation was supported by an *a priori* planned contrast, which compared the uncertainty monitoring EE feedback condition with the five other conditions, and confirmed the superiority of combining such a training method with such feedback to support transfer [$F(1, 176) = 77.01$, $p < .001$, $\eta p^2 = .304$]. A 2 training (uncertainty monitoring vs. forced response) x 3 feedback type (verification, EE, no feedback) ANOVA further revealed a significant main effect of feedback [$F(2, 176) = 117.78$, $p < .001$, $\eta p^2 = .572$] and training on test performance [$F(1, 176) = 20.718$, $p < .001$, $\eta p^2 = .105$], but the interaction was not significant [$F(2, 176) = 2.21$, $p = .113$, $\eta p^2 = .025$].

Test phase differences were also observed when participants were assessed on their ability to estimate pH level of test stimuli. Inspection of data suggests that the ability to estimate pH levels of test stimuli varied by training method and feedback type. Specifically, uncertainty monitoring training appeared to be more accurate than forced response training, with greatest accuracy observed in the EE feedback conditions (see Figure 29). This observation was supported by an *a priori* planned contrast which showed that the uncertainty monitoring with EE feedback condition was more accurate at estimating pH than the five other conditions [$F(2, 166) = 108.99$ $p < .001$, $\eta p^2 = .568$]. A two-way ANOVA with training (uncertainty monitoring vs. forced response) and feedback (verification, EE, no feedback) revealed a significant main effect of feedback type [$F(2, 166) = 21.823$, $p < .001$, $\eta p^2 = .208$] on pH accuracy, and a marginally significant effect of training method [$F(1, 166) = 3.177$, $p = .077$, $\eta p^2 = .019$]. The interaction was not significant [$F(1, 166) = .357$, $p = .700$, $\eta p^2 = .004$]. This suggests that while participants were generally able to transfer knowledge from training to test phase, the extent to which participants can transfer knowledge depends more on the type of feedback provided during training than the training method itself.

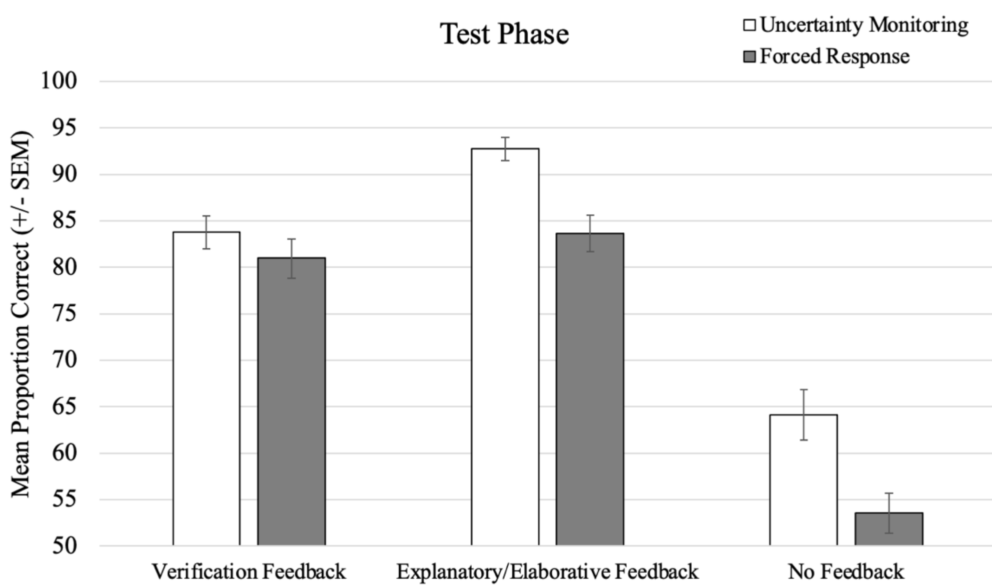


Figure 28. Performance for six training conditions during test phase on category accuracy.

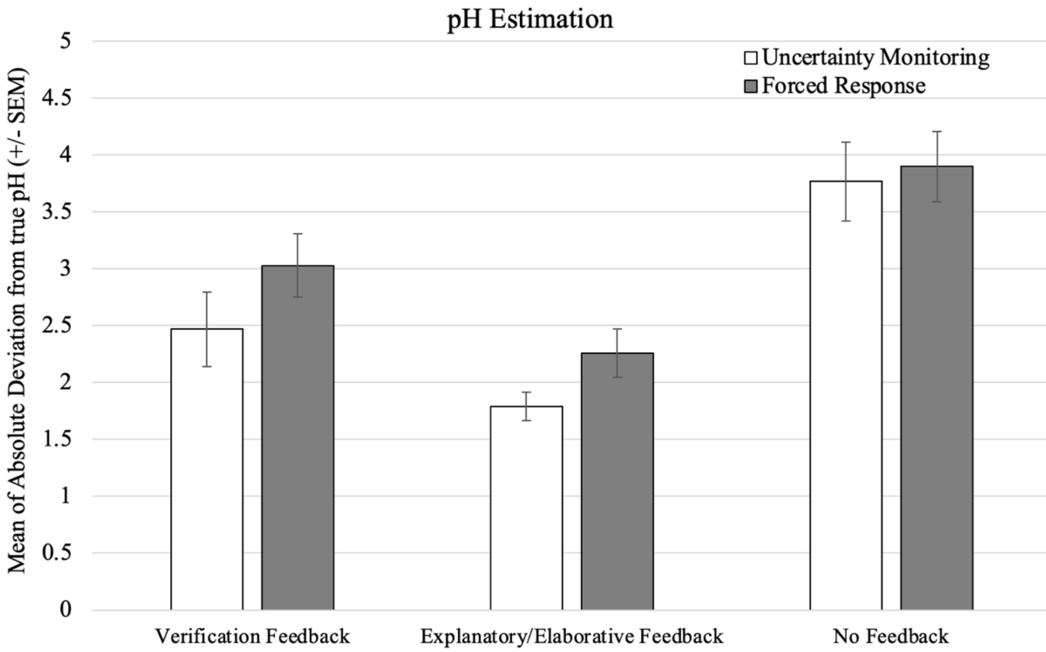


Figure 29. Accuracy for estimating pH levels of test stimuli for six training conditions. Lower scores indicate better accuracy.

Test Phase: Confidence

All participants displayed moderate levels of confidence during the test phase (see Figure 30). It was originally predicted that participants who were trained to monitor their uncertainty would evidence greater confidence at test. When examining the relationship between confidence and test performance, simple linear regressions suggests that participants' confidence was a significant predictor of performance as it accounted for a significant proportion of test accuracy (see Table 5) for the following conditions: Uncertainty Monitoring with Verification Feedback [R^2 = .161, F(1, 29) = 5.56, p = .025] (see Figure 31, left), and Uncertainty Monitoring with EE Feedback [R^2 = .193, F(1, 28) = 6.695, p = .015] (see Figure 31, right). However, a 2 training (uncertainty monitoring vs. forced response) x 2 feedback (verification, EE, no feedback) ANOVA did not find a significant main effect of training method [F(1, 176) = .019, p = .892,

$\eta p^2 = .000$] or feedback type [$F(2, 176) = 1.127$, $p = .326$, $\eta p^2 = .013$] on confidence during test phase. There was no significant interaction [$F(2, 176) = .109$, $p = .897$, $\eta p^2 = .001$].

Considering that confidence is impacted by feedback, it was not surprising that confidence was low during test phase as participants performed a novel task and did not receive any feedback. Lack of feedback may have made it difficult to monitor and judge performance which may have resulted in low test confidence. As an alternative measure of metacognition, we look at calibration accuracy during the test phase (below).

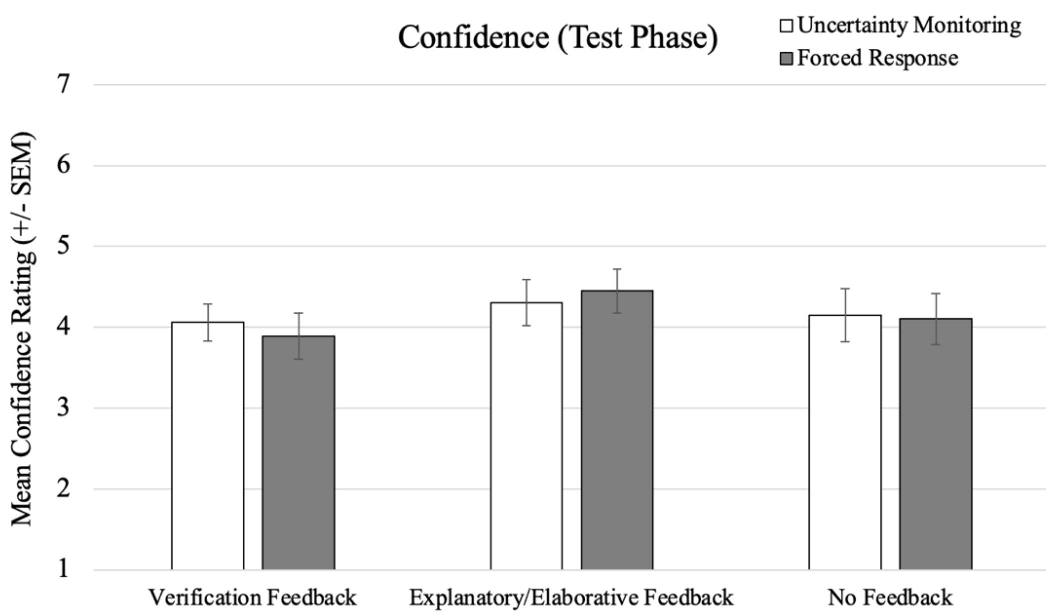


Figure 30. Average confidence rating during test phase.

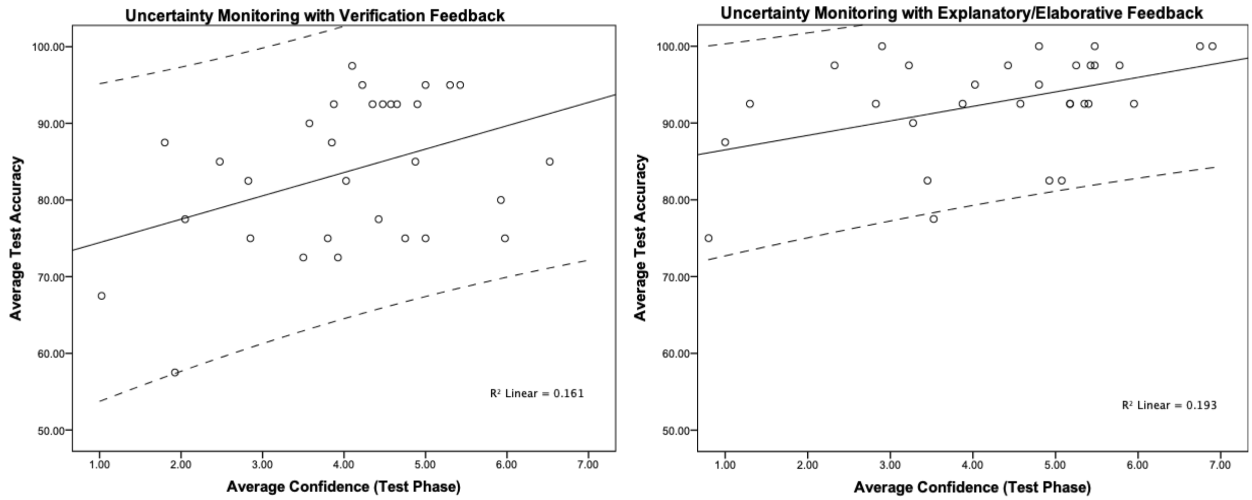


Figure 31. Average test phase accuracy by average confidence between: (Left) Uncertainty Monitoring with Verification Feedback, and (Right) Uncertainty Monitoring with Explanatory/Elaborative Feedback. Dashed lines represent 95% confidence interval bands.

Test Phase: Calibration Accuracy

Initial inspection of the data suggests that participants who were trained to monitor their uncertainty were generally better at assessing their performance during test phase (see Figure 32). Results from a 2 training methodology (uncertainty monitoring vs. forced response) x 3 feedback type (verification, EE, no feedback) ANOVA were consistent with the initial observation and prediction that calibration would be superior for participants in the uncertainty monitoring EE feedback condition, as an *a priori* planned contrast indicated an advantage for combining such a training method with such feedback [$F(2, 176) = 46.807$, $p < .001$, $\eta p^2 = .35$]. Further analysis revealed a significant main effect of feedback type [$F(2, 176) = 3.898$, $p = .022$, $\eta p^2 = .042$] and training method [$F(1, 176) = 6.088$, $p = .015$, $\eta p^2 = .033$] on calibration accuracy. The interaction was not significant [$F(2, 176) = .115$, $p = .892$, $\eta p^2 = .001$]. In sum, participants trained with either uncertainty monitoring or EE feedback generally evidenced greater calibration accuracy, which is indicative of greater metacognition.

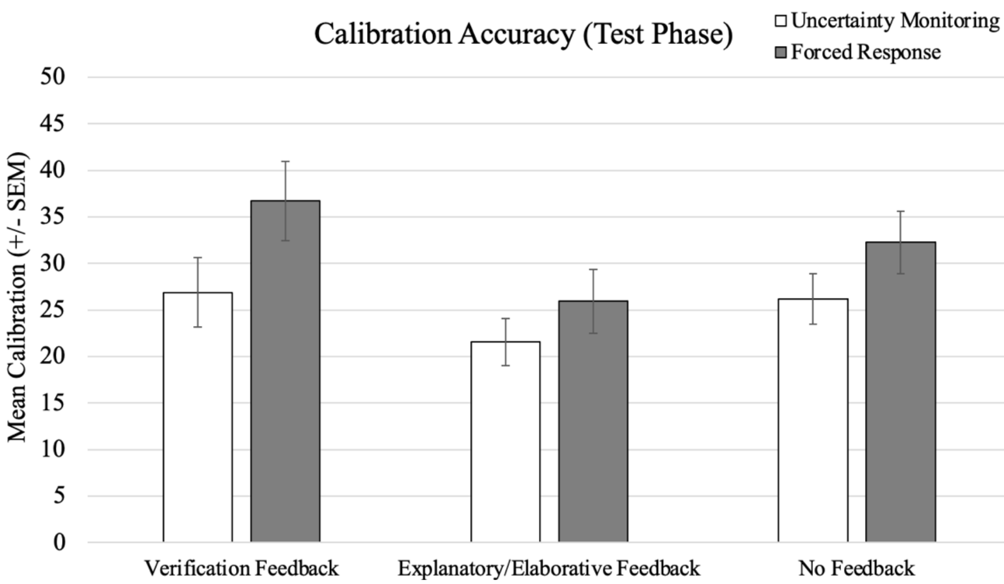


Figure 32. Average calibration accuracy between training methods by feedback type. Lower scores closer to zero indicate greater calibration accuracy.

Uncertainty Monitoring Training

Uncertainty was expected to decrease throughout the course of learning for participants in the uncertainty monitoring training condition. Paired sample t-tests supported the initial hypothesis that participants' uncertainty responses would significantly reduce throughout training (block 1 to block 2), specifically for participants who received verification feedback [$t(30)= 2.701$, $p = .011$] and EE feedback [$t(29)= 2.339$, $p = .026$], but not for those who did not receive feedback [$t(27)= 1.873$, $p = .072$]; see Figure 33.

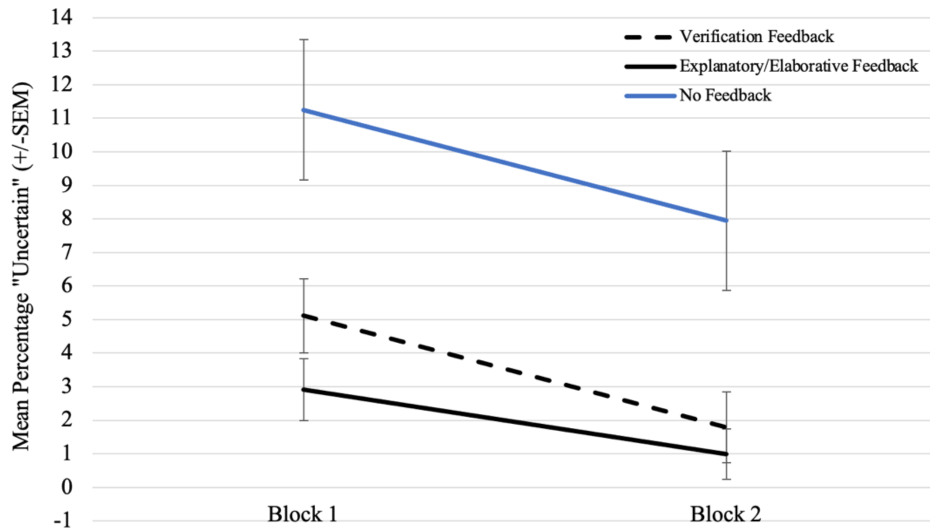


Figure 33. Average percentage of “Uncertain” responses between feedback conditions within the Uncertainty Monitoring training condition.

No Feedback Training Conditions

A primary question was whether performance differences observed in Experiments 1 and 2a were solely dependent upon feedback. If so, then removing feedback should eliminate those differences. However, if there is a benefit of uncertainty monitoring, then participants who have access to an uncertain response option should still outperform those who did not, even in the absence of feedback. Inspection of data suggest a general advantage of uncertainty monitoring training with no feedback, compared to forced response training with no feedback (see Figure 35). Independent samples t-test show that performance during test phase was superior for participants who were trained to monitor their uncertainty compared to forced response training [$t(57) = 3.075$, $p = .003$, $g = .801$]. However, these groups did not differ during training phase [$t(57) = .706$, $p = .483$, $g = .183$]; see Figure 34.

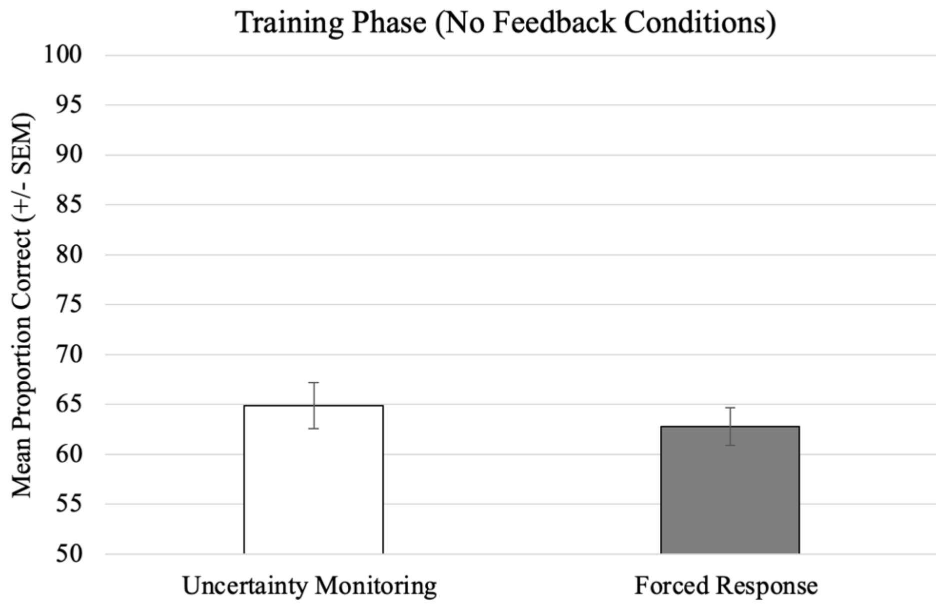


Figure 34. Average performance during training phase for participants who did not receive feedback.

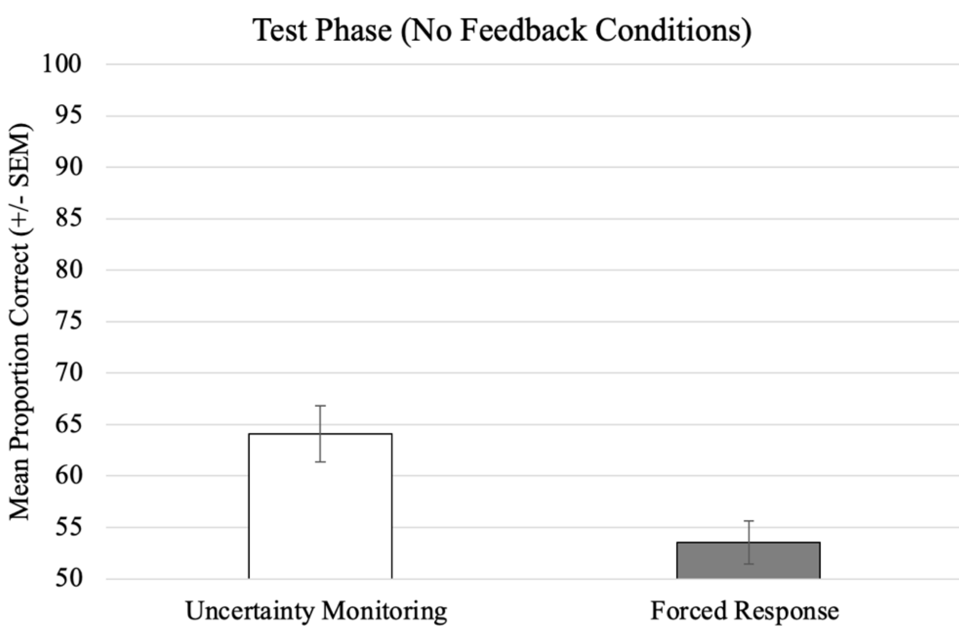


Figure 35. Average performance during test phase for participants who did not receive feedback.

Experiment 2b Discussion

The goal of Experiment 2b was to expand upon the results from Experiments 1 and 2a and further investigate the methodological factors that impact learning, as well as address limitations in Experiments 1 and 2a. Findings from the present experiment generally mirrored those from Experiment 2a and implicated a role for both training method and feedback type on performance, with performance being greater for those trained with Uncertainty Monitoring and EE feedback, particularly transfer performance. The results from this experiment are important for several reasons: 1) it demonstrated that aspects of metacognition, such as confidence and calibration accuracy, depend upon both training and feedback, 2) it showed that participants in the forced response condition were able to monitor and evaluate their performance to some degree, despite not having an option to report uncertainty, and 3) training participants to monitor their uncertainty can support transfer of knowledge to novel contexts even in the absence of feedback. It should be noted that the type of learning assessed in Experiments 1 and 2 can be considered explicit and dependent on a declarative memory system. It is unclear whether the expected benefits of uncertainty monitoring extend to different types of knowledge and memory systems.

CHAPTER 4

EXPERIMENT 3

Background

The goal of Experiment 3 was to investigate whether uncertainty monitoring can support implicit, nondeclarative learning as it did for explicit, declarative learning in Experiments 1 and 2. Despite much research suggesting that both explicit and implicit processes are involved with learning and metacognition (Koriat, 1997; Koriat, Nussinson, Bless, & Shaked, 2008; Reder 1987; Reder & Schunn, 1996), few studies have investigated uncertainty monitoring during nondeclarative tasks. Experiment 3 expanded upon the findings from Experiments 1 and 2 and investigated the role of metacognition and uncertainty monitoring during implicit learning.

The design of Experiment 3 was based upon the results from Experiments 1 and 2, which showed a general benefit of uncertainty monitoring on explicit learning. Experiment 3, however, utilized a different learning task and category structure (i.e., Shepard, Hovland, and Jenkins (SHJ), 1961) to assess implicit learning and tap into the implicit procedural-learning system (Smith, Minda, Washburn, 2004; Smith et al., 2012; Waldron & Ashby, 2001).

Metacognition and uncertainty monitoring are presumed to be impaired during implicit learning. Therefore, it was predicted that participants would report greater uncertainty and lower confidence during the initial stages of learning. However, because monitoring uncertainty and reporting confidence depends on awareness of one's own performance, the requirement of confidence reports was predicted to induce performance monitoring and increase task accuracy as performance monitoring has been shown to improve accuracy and confidence over time (Nelson & Narens, 1990; Nietfeld, Cao, & Osborne, 2006; Schoenherr & Logan, 2014). The primary goal of Experiment 3 was to investigate whether uncertainty monitoring could support implicit learning as it does explicit learning. Not only does Experiment 3 expand upon the findings of Experiments 1 and 2, but it is also one of few studies that investigate uncertainty monitoring during implicit, nondeclarative learning.

Method

Participants

Participants[10] (*N* = 61) were recruited from Amazon's Mechanical Turk. Amazon's Mechanical Turk is an online crowdsourcing platform, where researchers can post surveys and experiments for individuals to complete in exchange for monetary compensation. Participants that completed Experiment 3 were compensated with a flat rate of $2.00, and were at least 18 years of age, US High School Graduates, and had normal or corrected to normal vision (i.e., wear glasses/contacts if necessary). Participants were randomly assigned to one of two conditions: Uncertainty Monitoring condition (n = 30) and Control condition (n = 31). A total of 5 participants were excluded from analysis because they did not complete the experiment or were statistical outliers (i.e., more than 3 SD from the mean on average task accuracy in block 2). The remaining sample size by condition was Uncertainty Monitoring (n = 27) and Control (n = 29).

Stimuli

The stimuli consisted of eight unique objects that varied in size, shape, and color, as well as category membership (e.g., Category A or Category B) (see Figure 36). These stimuli were adapted from the SHJ Type IV structure (see Figure 2) and were used as a measure of implicit

[10] An *n* = 30 per condition was initially chosen as a conservative estimate based on previous literature on uncertainty monitoring and category learning within the implicit system (Koriat & Bjork, 2005; Minda, Desroches, & Church, 2008; Paul, Boomer, Smith, & Ashby, 2011). One additional participant was recruited because one participant did not complete the experiment and reported nonsensical and low-quality responses in the post-task questionnaire.

learning as the optimal strategy was difficult to verbalize, and accurate category membership required participants to attend to three features[11] (e.g., size, shape, and color).

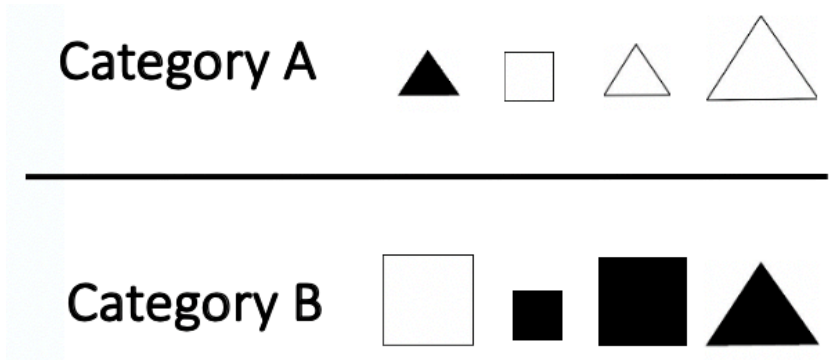


Figure 36. Example stimuli set for Experiment 3.

Procedure

All participants provided informed consent and were randomly assigned to one of two training conditions (e.g., Uncertainty Monitoring vs. Control). Participants completed two blocks of a learning task (64 trials each) which required participants to classify objects into two contrasting categories (e.g., Category A or B).

Uncertainty Monitoring Condition

Participants in the Uncertainty Monitoring condition were shown a single stimulus on the screen and were instructed to respond to the question, “Which category does this image belong to?” Participants then selected from the following options: Category A, Category B, or

[11] Another plausible strategy is to look at the overall similarity of stimuli, and explicitly memorize the exceptions to category rules (verbal rule: “White shapes (except the big square) and small black triangle belong in Category A; Black shapes (except small triangle) and big white square belong in Category B) (Nosofsky et al., 1994). There is research to suggest, however, that the Type IV structure is learned via an implicit process (Minda, Desroches, & Church, 2008; Waldron & Ashby, 2001) and is a suitable measure of implicit learning.

Uncertain, and were prompted to report their confidence in their responses on a Likert-type scale ranging from 1 (Not at all Confident) to 7 (Extremely Confident). After reporting their confidence, participants were provided verification feedback for their responses (e.g., "CORRECT: Category A" or "WRONG: Category A") (see Figure 37, top). Participants were told that incorrect answers would result in a 10 second "timeout" which delayed the start of the next trial, whereas selecting the correct answer, or "uncertain" option, allowed them to proceed to the next trial. At the end of the task, participants completed a post-task questionnaire that probed their decision-making strategies and perceived task performance on a 100-point scale. As with Experiments 1 and 2, the post-task questionnaire also included an attention check question to ensure participant engagement and data quality[12] (see Appendix C).

Control Condition

To assess the role of uncertainty monitoring on implicit learning, a control condition was implemented. The control condition included the same stimuli and task procedure as those used in the uncertainty monitoring condition. The control group, however, did not have the option to respond with "uncertain" during the task (see Figure 37, bottom).

[12] Attention check questions were also used to filter out potential "bots" on Amazon's Mechanical Turk platform.

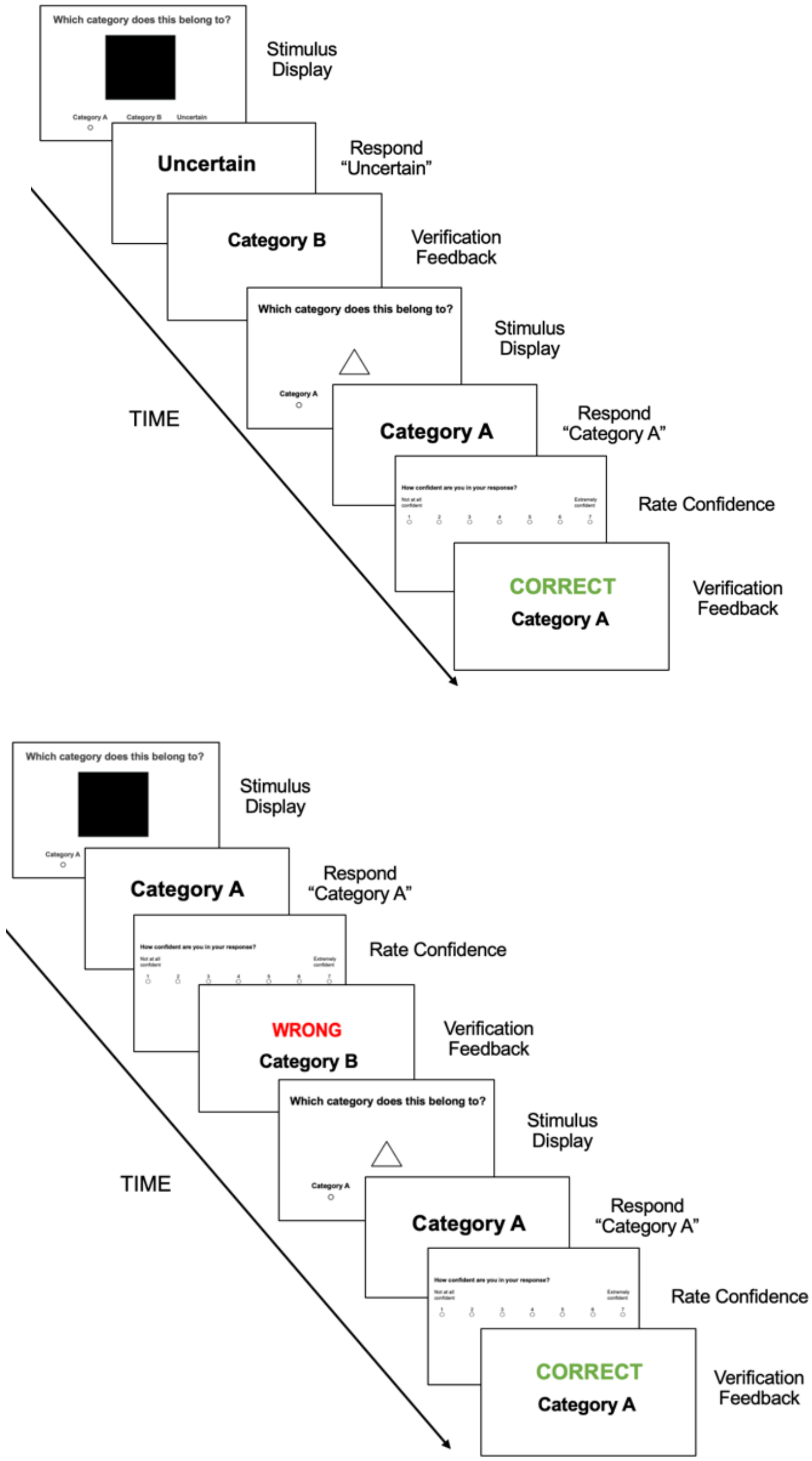


Figure 37. Example display for training conditions: (Top) Uncertainty Monitoring, and (Bottom) Control.

Data Analysis Procedure

Of particular interest is the role of uncertainty monitoring in implicit learning. The data was analyzed in the same manner as Experiments 1 and 2, where average task performance was calculated to compare task accuracy[13] between the uncertainty monitoring and control conditions across time. Confidence ratings were averaged for each task block and compared between groups. As an additional measure of metacognition, calibration between participants' perceived performance and actual performance were assessed.

Results

Task Performance

The results were similar to Experiments 1 and 2. Learning was evident in both training conditions, with task accuracy being generally higher for the Uncertainty Monitoring condition (see Figure 38). Consistent with this observation, *a priori* planned comparisons show that task accuracy in block 1 was higher for participants who were trained in the uncertainty monitoring condition compared to control condition [$F(1, 54) = 5.021$, $p = .029$, $\eta p^2 = .085$]. However, no differences were observed in block 2 [$F(1, 54) = .962$, $p = .331$, $\eta p^2 = .018$]. More generally, a 2 training method (uncertainty vs. control) x 2 time (block 1 vs. block 2) ANOVA revealed a significant main effect of training method [$F(1, 54) = 4.61$, $p = .034$, $\eta p^2 = .041$] and time [$F(1, 54) = 17.79$, $p < .001$, $\eta p^2 = .141$] on task performance. However, the interaction was not significant [$F(1, 54) = .354$, $p = .553$, $\eta p^2 = .003$]. These data suggest that there was a slight benefit of uncertainty monitoring training during the initial stages of learning. Accuracy was

[13] As with Experiments 1 and 2, task accuracy was adjusted for participants in the Uncertainty Monitoring condition in Experiment 3. Only categorical responses were included, while "uncertain" response trials were excluded from calculation.

generally higher and increased more quickly in the uncertainty monitoring condition, but group differences did not remain when learning was complete.

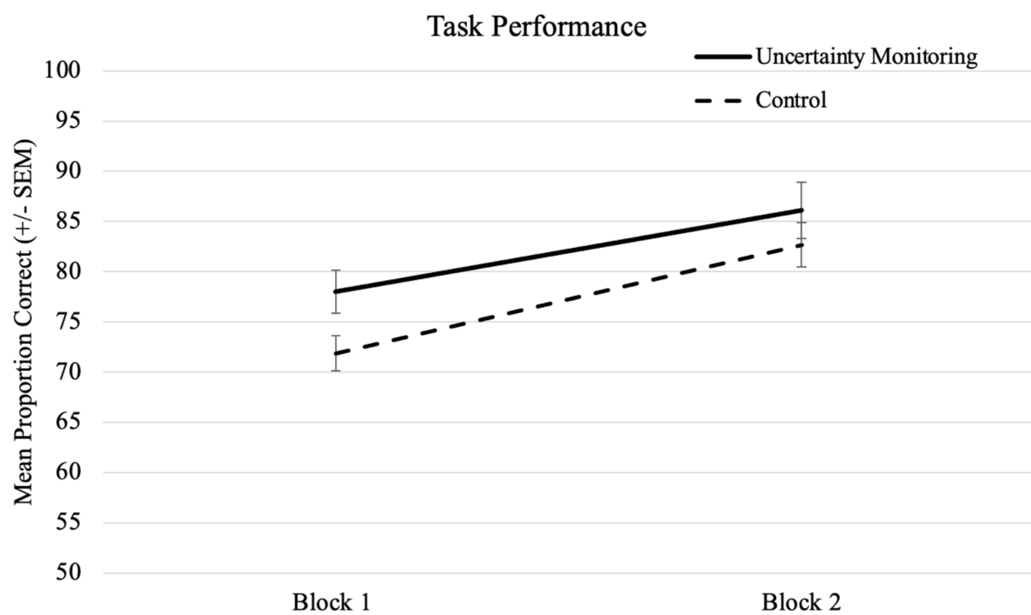


Figure 38. Performance between training conditions on category accuracy. Figure depicts adjusted scores for the Uncertainty Monitoring condition.

Confidence

Previous research shows that monitoring uncertainty can improve confidence and judgment of performance. It was initially predicted that the uncertainty monitoring condition would report greater confidence relative to the control condition. These predictions were supported by an *a priori* planned contrast which indicated that confidence was significantly higher for participants in the uncertainty monitoring condition compared to controls in both block 1 [$F(1, 54) = 7.194$, $p = .010$, $\eta p^2 = .118$] and block 2 of the task [$F(1, 54) = 6.556$, $p = .014$, $\eta p^2 = .108$] (see Figure 39). A two-way ANOVA indicated a significant main effect of training [$F(1, 54) = 13.749$, $p < .001$, $\eta p^2 = .113$] and time [$F(1, 54) = 7.658$, $p = .007$, $\eta p^2 = .066$] on confidence. There was no significant interaction [$F(1, 54) = .031$, $p = .861$, $\eta p^2 = .000$].

When examining the relationship between confidence and performance, a linear regression showed that confidence was a significant predictor of performance as it accounted for a significant proportion of task accuracy for the Uncertainty Monitoring condition [$R^2 = .200$, $F(1, 25) = 6.245$, $p = .019$] but not the control condition [$R^2 = .020$, $F(1, 27) = .549$, $p = .465$] (see Table 6, and Figure 40). These results mirror those from Experiment 2b, which show that confidence not only increases with learning, but uncertainty monitoring training increases confidence, which in turn may improve performance.

Table 6. Regression Analysis summary for confidence predicting performance in Experiment 3.

		Unstandardized Coefficients		**Standardized Coefficients**		
Training Condition	***df***	**B**	***SE***	**β**	***t***	***p***
Uncertainty Monitoring Condition	25	7.79	3.117	0.447	2.499	0.019
Control Condition	27	1.228	1.657	0.141	0.741	0.465

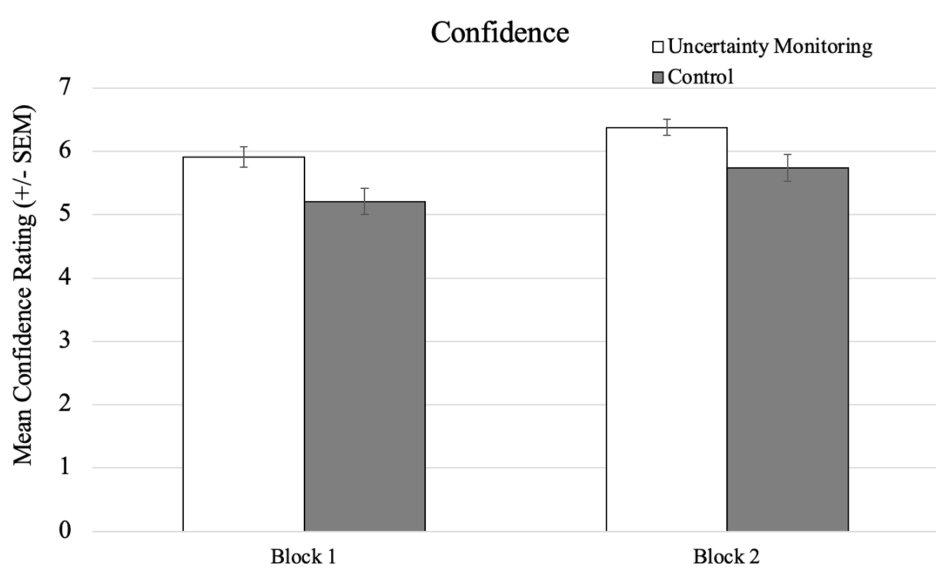


Figure 39. Average confidence by training method.

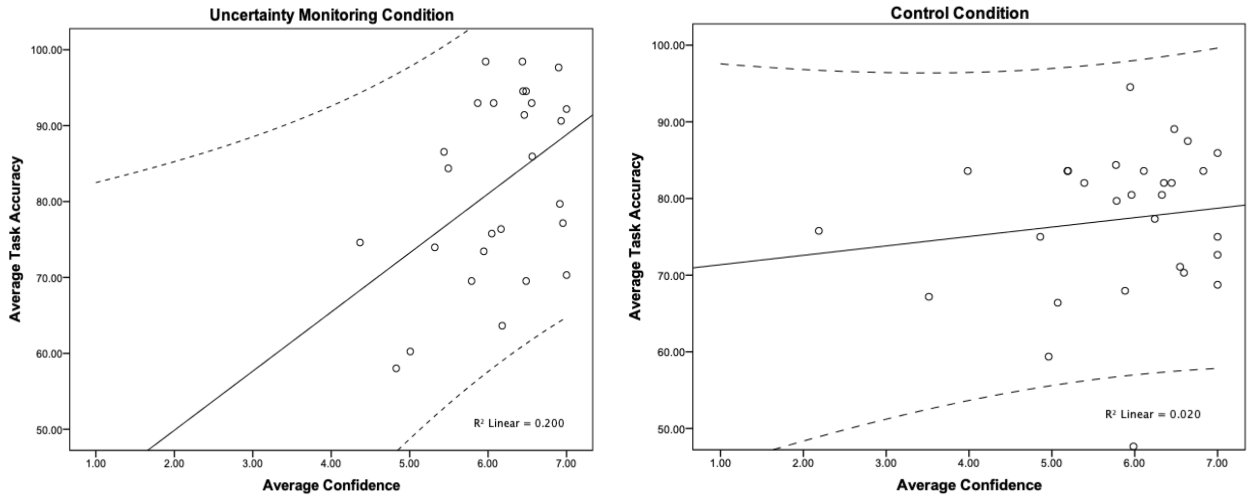


Figure 40. Average task accuracy by average confidence between: (Left) Uncertainty Monitoring condition and (Right) Control condition. Dashed lines represent 95% confidence intervals.

Calibration Accuracy

It was predicted that the uncertainty monitoring condition would have greater calibration accuracy compared to controls. Inspection of data suggests that the uncertainty monitoring condition was generally more accurate in judging their performance (see Figure 41). Results, however, did not support these hypotheses as *a priori* planned contrasts did not detect differences in calibration accuracy between the two training conditions in either block 1 [$F(1, 54) = .042$, $p = .839$, $\eta p^2 = .001$] or block 2 of the task [$F(1, 54) = 2.649$, $p = .109$, $\eta p^2 = .047$]. Further analysis using a 2 training method (uncertainty vs. control) x 2 time (block 1 vs. block 2) ANOVA, showed no significant main effects of training method [$F(1, 54) = 1.213$, $p = .273$, $\eta p^2 = .011$] or time [$F(1, 54) = .002$, $p = .962$, $\eta p^2 = .000$] on calibration accuracy. The interaction was not significant [$F(1, 54) = .587$, $p = .445$, $\eta p^2 = .005$].

Interestingly, although results were not statistically significant, perceived performance increased for the uncertainty monitoring condition in block 2, whereas perceived performance decreased for the control condition. This may suggest that over time participants in the uncertainty monitoring condition became more confident and overestimated their performance, whereas the control condition became less confident and underestimated their performance. This is compatible with a similar pattern observed in participants' confidence.

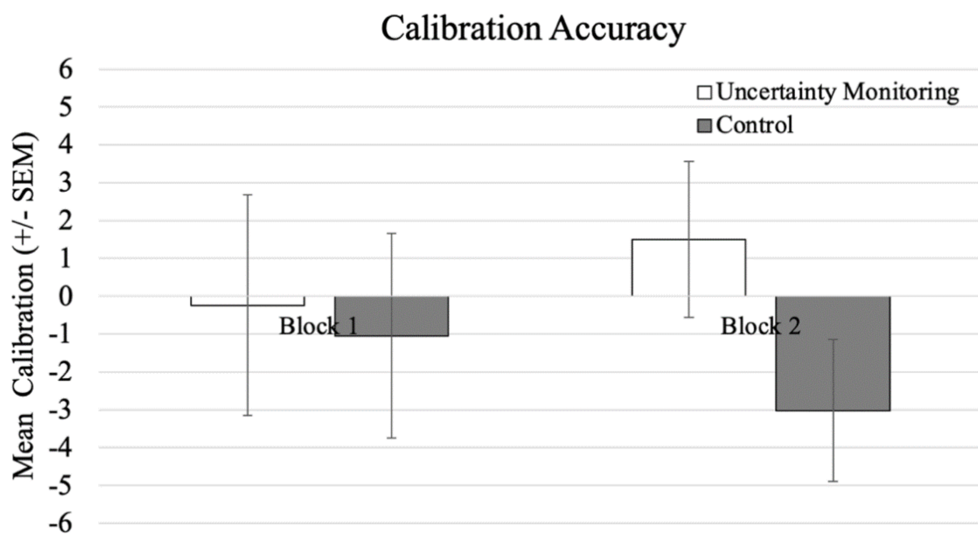


Figure 41. Average calibration accuracy between training methods by block. Calibration was computed by taking the difference between participants' judgments of performance and their actual performance (lower scores closer to zero indicate greater calibration accuracy).

Uncertainty Monitoring Training

A primary question in Experiment 3 was whether it was possible for participants to monitor uncertainty during implicit, nondeclarative tasks. It was expected that uncertainty would be highest during the initial stages of learning and would decrease over time. Paired sample t-test supported this hypothesis as uncertainty responding significantly decreased throughout the task (block 1 to block 2) for the Uncertainty Monitoring condition; $t(26) = 3.456$, $p = .002$, Figure 42.

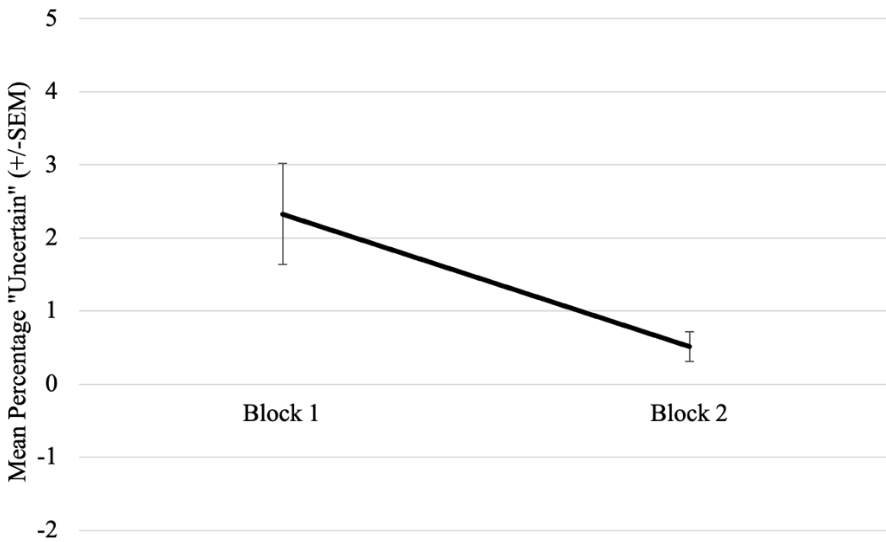


Figure 42. Average percentage of “uncertain” responses for Uncertainty Monitoring condition.

Experiment 3 Discussion

The primary goal of Experiment 3 was to investigate whether uncertainty monitoring could support implicit learning as it did with explicit learning in Experiments 1 and 2. Metacognition and uncertainty monitoring are often presumed to be impaired during implicit learning, as such processes are thought to be hidden from conscious monitoring and evaluation. The inability to consciously monitor one’s own performance, as illustrated by previous work, would have been apparent if task accuracy and confidence were similar between the two training conditions. Contrary to the literature, task accuracy and confidence were generally higher in the uncertainty monitoring condition compared to the control condition. Recall, the only difference between the two training conditions was the option to report uncertainty. It is possible that the addition of an uncertain response option may support learning and monitoring of performance, as participants in the uncertainty monitoring condition learned more quickly and expressed higher confidence in their abilities compared to the control condition. It should be noted, however, that differences in performance were mainly observed during the initial stages of learning. Thus, while uncertainty monitoring seems to be possible during implicit learning, such metacognitive processes may benefit explicit learning more.

CHAPTER 5

GENERAL DISCUSSION

The present dissertation was designed to explore a relatively understudied sector in the cognition and education literature, as it investigated the role of uncertainty monitoring in category learning. Experiment 1 of this dissertation used a categorization task to investigate how uncertainty monitoring impacted learning and transfer of Chemistry concepts. Experiment 2 further examined the training factors that impact learning and assessed the role of feedback and uncertainty monitoring on performance. Experiment 3 investigated whether uncertainty monitoring differentially impacts implicit learning as compared to explicit learning. The results from Experiment 1 showed a benefit of uncertainty monitoring during category learning and transfer. Results from Experiment 2 supported those findings and revealed that while performance may depend upon feedback type, there was an overall benefit of uncertainty monitoring on confidence and performance. The results from Experiment 3 show that metacognitive processes such as uncertainty monitoring is possible during implicit learning but may be better suited for supporting explicit learning, as benefits were only observed during the initial stages of implicit learning. Taken altogether, the results from the three experiments provide support for a general benefit of uncertainty monitoring on learning and transfer.

Summary

Experiment 1

Metacognitive processes such as monitoring uncertainty have been shown to enhance learning outcomes (Paris et al., 1988; Paris & Winogran, 1990; Ricky & Stacy, 2000; Vaidya, 1999). Thus, a prediction for an advantage of uncertainty monitoring training was based on previous research implicating the benefits of metacognition. Although both training methods supported test performance on a novel task, there was a clear advantage of uncertainty monitoring training on transfer compared to forced response training. The uncertainty monitoring condition consistently scored higher on category accuracy and confidence during the test phase. Contrary to hypotheses, however, accuracy on pH estimation did not differ between training conditions. This may be because participants only learned the colors that corresponded with category membership, but not pH level.

In addition, participants who were given the option to report uncertainty were able to access explanatory and elaborative feedback if they selected the "uncertain" response option. A concern was whether performance differences were due to feedback type between the two conditions, rather than differences in metacognitive processes. Moreover, while participants in the forced response condition were not given the option to report uncertainty, it is possible that participants were still monitoring their performance in this condition.

In sum, the results show an overall benefit of uncertainty monitoring as it supported learning and transfer. To my knowledge, Experiment 1 is one of few studies to have assessed the impact of uncertainty monitoring in the context of category learning in education.

Experiment 2

Experiment 2 was designed to address two questions. First, was the advantage observed in Experiment 1 due to uncertainty monitoring training or feedback type? To ensure that it was the former, feedback was matched across training conditions in Experiment 2, which included two additional training conditions where feedback was withheld. Second, do participants in the forced response condition monitor their learning and uncertainty despite not having the option to report uncertainty? Trial-by-trial confidence ratings were implemented throughout Experiment 2 and were used to assess participants' ability to monitor and judge their own performance.

Confidence reports provided a direct comparison between subjective confidence and actual task accuracy, which has been shown to induce performance monitoring (Nelson & Narens, 1990; Nietfeld, Cao, & Osborne, 2006; Schoenherr & Logan, 2014). Given that uncertainty monitoring has seldom been studied in categorization literature, a replication of the benefits of uncertainty monitoring on category learning would substantiate findings from Experiment 1 and elucidate the methodological factors that impact learning and transfer.

The results from Experiment 2 again revealed an advantage for uncertainty monitoring training, even when feedback was matched between conditions. As predicted, feedback played a significant role in performance as explanatory and elaborative feedback improved learning and confidence across training methods compared to verification or no feedback. Results suggest that participants in the forced response condition were able to judge and evaluate their performance despite not having an option to report uncertainty.

These findings demonstrate that various aspects of metacognition, including confidence and calibration accuracy, may depend upon both training and feedback. However, the extent to which participants could transfer learning was impacted by training as uncertainty monitoring training consistently supported test phase performance, as transfer was superior in this condition even in the absence of feedback. Thus, the replication with adjustments to feedback type ensured that results from Experiment 1 were not solely driven by differences in feedback, but rather a combination of training factors that support the monitoring of uncertainty as well as addressing uncertainty.

Experiment 3

Experiment 3 was designed to extend the findings from Experiments 1 and 2 by investigating the impact of uncertainty monitoring on a different task that is thought to tap into a different learning system. Unlike Experiments 1 and 2, which focused on explicit learning, Experiment 3 examined implicit learning using a different category learning task that is thought to depend on the implicit procedural-learning system. The primary question for Experiment 3 was whether uncertainty monitoring also benefits implicit learning as it did for explicit learning. To investigate this, Experiment 3 included an experimental condition where participants could report uncertainty throughout the task and compared it to a control condition in which participants did not have the option to report uncertainty.

The results suggest that access to uncertainty monitoring training generally supported learning and confidence. As predicted, confidence was greater in the uncertainty monitoring condition compared to the control condition. However, when comparing subjective performance with actual performance, there were no differences in calibration accuracy between the two conditions. An interesting finding, however, was that higher performing participants in the uncertainty monitoring condition reported lower scores compared to lower performing participants who reported higher scores. This is explained by metacognition and categorization literature which posit that elements of implicit learning may be hidden from conscious evaluation, such that individuals may express a disbelief in their ability to perform a task.

While uncertainty monitoring training appeared to benefit task accuracy during the initial stages of learning, there were no differences in accuracy between conditions at later stages of learning. These results suggest that although uncertainty monitoring may be possible during implicit learning, it may be better suited for explicit learning.

Metacognition and Uncertainty Monitoring on Category Learning

Previous studies have revealed that metacognition and uncertainty monitoring have a profound impact on student performance (Ashdown & Simic, 2000; Gersten, Jordan, & Flojo, 2005; Koriat, 1997; O'Dwyer & Childs, 2014; Regan, Childs, & Hayes, 2011; Stieff, 2011). They have been shown to help with judgment of learning (Callender, Franco-Watkins, & Roberts, 2015; Nietfeld, Cao, & Osborne, 2005; 2006), regulation of learning (Isaacson & Fujita, 2006; Sperling et al., 2004), and transfer of knowledge (Paris et al., 1988; Paris & Winogran, 1990; Ricky & Stacy, 2000; Vaidya, 1999).

Despite the research suggesting that uncertainty monitoring improves learning, such metacognitive processes have been underexplored within the field of categorization. Additionally, while many disciplines require learning fundamental categories, the impact of metacognitive processes on category learning has been relatively understudied within the context of education. Thus, a major theme of the present dissertation was how uncertainty monitoring could be promoted and used to improve learning. Given that uncertainty arises at various points throughout the learning process, all three experiments in this dissertation were designed to address participant uncertainty in real-time and further investigate the role of uncertainty monitoring on performance.

A primary question was how participants would utilize an uncertain response option and whether its use impacted performance. Given the research suggesting that uncertainty monitoring improves learning, it was predicted that participants who were trained to monitor their uncertainty would have greater task accuracy in Experiments 1 and 2. In Experiment 1, participants in the uncertainty monitoring condition outperformed those in the forced response condition, as training and test phase accuracy was superior for participants who had access to and utilized an uncertain response option. Experiment 2 replicated the findings from Experiment 1, and further investigated the effect of uncertainty monitoring training by matching the type of feedback provided across training conditions. Results from Experiment 2 suggest that uncertainty monitoring generally supports learning, however, other factors may also impact performance including task feedback and participant confidence.

The effect of uncertainty monitoring training was not as apparent in Experiment 3, however. Considering that the present dissertation is one of few studies to assess uncertainty monitoring in category learning, it is possible that the benefits of uncertainty monitoring is limited to certain types of learning and may only benefit some aspects of performance.

The Role of Feedback

Performance was also impacted by different types of feedback. For example, explanatory and elaborative (EE) feedback is thought to help students develop a deeper understanding of information relative to simple verification feedback (Butler et al., 2013; Fazio, Huelser, Johnson, & Marsh, 2010; Pashler, Cepeda, Wixted, & Rohrer, 2005). A concern in Experiment 1 was the difference in feedback type between training conditions as participants in the uncertainty monitoring condition were provided EE feedback for the "uncertain" responses. Experiment 2 addressed this issue and investigated the role of feedback on performance by matching feedback between training conditions.

Changing the type of feedback participants received could have impacted the results in many ways. For instance, in Experiment 1, participants who received EE feedback for uncertainty responses were more likely to learn the rules and stimulus features necessary for category membership at a faster rate, and to a greater degree, than those trained with verification feedback. It is possible that changing the type of feedback to verification feedback may slow down learning progress, and lower performance for those in the uncertainty monitoring condition. Participants may not have thoroughly understood why a stimulus belonged in a specific category and may have committed errors throughout training, which could have transferred into the test phase. The opposite effect is possible when switching from verification feedback to EE feedback, which may have improved performance and accelerated the learning of task rules and features for participants in the forced response conditions.

Furthermore, the type of feedback provided in Experiment 1 may have been a motivator for participants to select the “uncertain” response option to acquire additional information, rather than to monitor their uncertainty. Providing simple and discrete verification feedback over more elaborative feedback may cause participants to feel less inclined to report uncertainty and lead them to guess the answers instead. Likewise, providing EE feedback for all task responses may reduce the likelihood of participants selecting the “uncertain” response option, as it provided no additional information over categorical responses. If this was the case, then utilization of the “uncertain” response option should have decreased in Experiment 2a or would have been reserved for more difficult trials as participants are often reluctant to give uncertainty responses but may do so adaptively to decline answering difficult trials (Paul et al., 2011). Thus, it is possible that by changing the type of feedback provided, the use of the uncertain response option and its utility may have changed as well. However, considering that Experiment 2a provided participants with feedback for all task responses—including uncertainty responses—this approach may have continued to incentivize uncertainty responding. In addition, it addressed uncertainty without giving an advantage to either training condition, as all task responses elicited the same feedback type within their respective training conditions.

Training and feedback may also impact confidence and judgment of learning (Callender, Franco-Watkins, & Roberts, 2015; Nietfeld, Cao, & Osborne, 2005, 2006; Renner & Renner, 2001). Detailed feedback, such as EE feedback, may increase confidence in task knowledge and task performance relative to simple verification feedback. Considering that training metacognitive skills such as uncertainty monitoring have been shown to improve confidence and judgment of performance, it was not surprising that confidence was highest for participants who were trained on both uncertainty monitoring and EE feedback in Experiment 2a and 2b. The section below further discusses this relationship.

Metacognition on Subjective and Objective Performance

Confidence

Previous studies show that subjective performance, such as feelings of confidence and doubt, may lead people to respond appropriately to those feelings. Monitoring and controlling these cognitive processes form the basis for metacognition and uncertainty monitoring literature. As such, confidence has been used as an indicator of metacognition in education and cognition research (Renner & Renner, 2001; Schoenherr & Lacroix, 2020, respectively). In both lines of work, confidence has been shown to be correlated with learning and performance monitoring.

Each experiment in this dissertation included trial-by-trial confidence ratings during a categorization task. The results from Experiments 1 and 2a, however, did not support initial predictions of higher confidence following uncertainty monitoring training. This could have been due to the fact that confidence was assessed post-training during the test phase. Considering that the test phase required participants to transfer knowledge from the training phase, it was reasonable to assume that upon completion of training, participants were generally more confident in their task knowledge. As such, Experiments 2b and 3 assessed confidence throughout the entire experiment, from training to test phase.

Results from Experiment 2b generally aligned with the literature, as participants who were trained to monitor their uncertainty consistently reported higher levels of confidence and greater task accuracy. However, upon further inspection of the data, this result may have been due to the type of feedback provided to participants in Experiment 2b. Recall, there were three feedback types: verification, explanatory/elaborative, and no feedback. Participants who received EE feedback had higher confidence and accuracy than verification and no feedback conditions. Although confidence and learning were generally greater for those trained with uncertainty monitoring and EE feedback, the results here are not enough to strongly suggest that uncertainty monitoring was the reason for greater confidence and task accuracy. Additionally, results from Experiment 3 suggest that confidence was higher for those trained in the uncertainty monitoring condition compared to control condition; however, there were no pronounced differences in learning between training conditions. These findings suggest that while various aspects of metacognition may impact performance, self-assessment and the ability to monitor ongoing states of uncertainty may be impacted by other training factors.

It is important to reiterate that not all participants in the experiments had the option to report uncertainty. Despite this, participants may have still engaged in metacognitive processes. Confidence was used as an additional measure of metacognition, as it provided a means to gauge metacognitive monitoring in participants who did not have the option to report uncertainty. Confidence ratings were used to assess participants' ability to monitor their own learning, as it provided participants with a direct comparison between subjective response confidence and actual response accuracy (e.g., task feedback). This is thought to impact learning as confidence reports may induce performance monitoring (Balakrishnan & Ratcliff, 1996), improve performance (Nelson & Narens, 1990; Schoenherr & Logan, 2014) and increase confidence (Nietfeld, Cao, & Osborne, 2006). Results from Experiments 1 and 2 supported this as higher confidence predicted greater task accuracy for all training conditions. In Experiment 3, this was only observed in the uncertainty monitoring condition but not the control condition.

It also remains possible that confidence is not a perfect indicator of metacognition and performance. For example, previous research shows that learners may feel overconfident in their poor performance as a result of inaccurate self-assessment in their abilities (Callender et al., 2015; Metcalfe & Finn, 2008). Likewise, learners may monitor their uncertainty and still report feeling under-confident in their abilities, despite high accuracy. Thus, the relationship between confidence and performance may not be so straightforward.

Calibration

Metacognition and uncertainty monitoring have also been measured by comparing people's judgments of their own performance with their actual performance. Accurate calibration between the two has been used as another indicator for greater metacognition in education and metacognition research (Callender, Franco-Watkins, & Roberts, 2015; Lundeberg et al., 1994; Nietfield, Cao, & Osborne, 2006). Studies show that good metacognition enables learners to accurately perceive their performance and identify their failures, whereas poor metacognition may result in overestimation of one's abilities. Given this, calibration accuracy was implemented and used as an additional measure for metacognition in Experiments 2b and 3.

Based on the literature, it was predicted that participants who had the option to report uncertainty would evidence greater calibration accuracy. The results from Experiments 2b generally aligned with the literature as participants who were trained to monitor their uncertainty had overall better calibration compared to other training methods (see Appendix D, Figure 43, top row). Results from Experiment 2b also indicated that feedback played a role in calibration, as participants who were provided with explanatory and elaborative feedback were more accurate in their judgments of performance, compared to other feedback types. In contrast, results from Experiment 3 did not show any differences in calibration between the uncertainty monitoring and control conditions (see Appendix D, Figure 43, bottom row). This could be because calibration accuracy requires participants to be aware and able to judge their own performance. As previously mentioned, the task used in Experiment 3 may not allow for that as implicit tasks are typically performed without awareness (Ashby et al., 1998; Reber, 1967; Squire & Wixted, 2011; Seger, 2010). Thus, the implications for these results are twofold. One, it supports the literature that calibration as a measure of metacognition can indeed improve with metacognitive and uncertainty monitoring training. Two, the extent to which uncertainty monitoring training benefits calibration, and performance in general, are limited to certain types of learning that allow for metacognitive awareness.

Learning and Memory Systems

The differences observed in Experiments 1 and 2 compared to Experiment 3 may be due to the nature of the tasks themselves. The results from Experiment 3 did not show the same effect of uncertainty monitoring on task accuracy, confidence, and calibration accuracy as it did in Experiments 1 and 2. This is likely due to the different types of learning systems recruited for the tasks used in Experiments 1 and 2, and Experiment 3. For instance, the task used in Experiments 1 and 2 is thought to depend upon an explicit, declarative system. Participants in Experiments 1 and 2 learned to classify objects by discovering categorical rules, which could be verbalized easily. The act of verbalizing a rule is characteristic of explicit category learning. In contrast, the task used in Experiment 3 is thought to depend upon an implicit, nondeclarative system. Participants in Experiment 3 also learned to classify objects, but unlike Experiments 1 and 2, there was no easily verbalizable rule, rather it required more procedural learning.

It is well established that humans are able to accurately monitor their cognitive processes during tasks that require an explicit, declarative system. In contrast, literature suggests that implicit processes are hidden from conscious monitoring and evaluation. Learners often express a lack of task knowledge, low-confidence, and poor performance despite progressive improvements in accuracy. This dissociation has been observed in early research on implicit learning within the field of cognitive neuroscience (Brooks, 1978; Knowlton, Mangels, & Squire, 1996; Reber, 1967), as well as metacognition and education (Dienes & Seth, 2009; Handel & Fritzsche, 2015; Persaud, McLeod, & Cowey, 2007). The studies all demonstrated a failure of metacognition and uncertainty monitoring during tasks that require implicit cognitive processes. Thus, the results from Experiment 3 may be explained by how various cognitive processes operate at the conscious and unconscious level.

The present dissertation previously presented theories on explicit and implicit metacognition on performance. A primary goal of Experiment 3 was to investigate whether learners could engage in metacognitive processes during implicit tasks. Much of the literature on metacognition posit that uncertainty monitoring is a relatively explicit process. The few studies that have examined uncertainty monitoring during category learning suggest that metacognition may be possible during implicit tasks; however, the knowledge acquired, and strategies used may be explicit in nature (Paul et al., 2011). That is, while learners may appear to monitor their uncertainty and utilize an uncertain response option, it is unclear whether participants did so because they were monitoring their performance or simply declining to complete difficult trials. This has been observed in prior research (Paul et al., 2011) and poses as a limitation in Experiment 3 of the present work (discussed below).

One goal of this thesis was to investigate the extent to which uncertainty monitoring can support different types of learning. Findings from this dissertation suggest there are implicit components of metacognition, but uncertainty monitoring may operate more efficiently on an explicit level. In fact, implicit metacognition may not provide as much benefit to knowledge acquisition as it is thought to occur at later stages of learning, typically after learning is complete (Koriat, 1997; Koriat, Nussinson, Bless, & Shaked, 2008). Furthermore, metacognition is inherently a conscious and explicit process that requires awareness of performance. A task that is designed to tap into an implicit, nondeclarative system would likely disrupt metacognitive processes, or void them entirely, as these types of tasks are presumed to be learned unconsciously and procedurally. While uncertainty monitoring may benefit explicit learning as observed in Experiments 1 and 2, results from Experiment 3 suggest that these benefits likely do not extend to implicit learning or at least not to the same degree.

Limitations

Experiments 1 and 2

A potential limitation in Experiments 1 and 2 is the population studied. Participants were undergraduate students enrolled in a psychology course. It is possible that the nature of the chemistry categories may have impacted performance, as participants may lack the background and training necessary for the task. It is possible that this could have led to uncertainty responding during the experiment. In addition, results may have been different if participants were majoring in chemistry. It would be expected that background knowledge of the subject matter would lead to less uncertainty responding and greater performance. However, the task used in Experiments 1 and 2 did not require background knowledge as the goal was to learn throughout the experiment.

It should be noted, however, that some participants did possess some background knowledge of the chemistry concepts (e.g., Acids and Bases). This was anticipated during the initial design of the study. Thus, to assess this all participants were probed about their knowledge of chemistry concepts (see Appendices A and B). Participants were instructed to rate their understanding of Acidity and Basicity on a scale from 1 to 5 (e.g., 1 = Very Low, 2 = Low, 3 = Average, 4 = High, 5 = Very High). On average, participants in both Experiments 1 and 2 reported "low" levels of familiarity and prior knowledge for the concepts of Acidity and Basicity at the start of the task. After completing the task, participants in the uncertainty monitoring condition rated their understanding for the concepts of Acidity and Basicity as "average", whereas the forced response condition reported an "average" level of understanding for Acidity but "low" understanding of Basicity. Thus, the baseline of knowledge for these chemistry concepts were initially low (but not zero), and generally improved following training. It is possible that the results would have been different with the exclusion of participants who possessed any prior knowledge of chemistry concepts.

Additionally, the categorization task used in Experiments 1 and 2 required that participants paid attention to the color outlines of the task stimuli. Although participants were required to have normal or corrected normal vision to participate in the experiments, the study did not control for participants with color blindness. Color blindness is the inability to detect differences in color. While it rarely results in complete lack of color vision (National Eye institute, 2019), a limitation in Experiments 1 and 2 is that it did not control for participants with color vision deficiencies, which could have impaired task performance.

Another potential limitation is the possibility of time-related confounds in the data. For example, Experiments 1, 2a, and 2b were conducted at different time points during a global pandemic (i.e., COVID-19). Inspection of the data across time show that participants' performance differed slightly from Experiment 1 to Experiments 2a and 2b. Although the data are from different participants, it appears that those who were trained in the original uncertainty monitoring condition in Experiment 1 (Fall 2020) had slightly higher task accuracy during training phase compared to participants who were trained in the same condition in Experiments 2a and 2b (Fall 2021 and Spring 2022, respectively). These differences may potentially be explained by the drastic changes and shifts in society during the time of data collection.

Experiment 3

Experiment 3 had its own limitations as well. One being population, as it recruited participants from a different population than that of Experiments 1 and 2. Experiments 1 and 2 recruited undergraduate students from the University of Maine, whereas Experiment 3 recruited participants from Amazon's Mechanical Turk. Despite differences in recruitment methods, the samples were closely matched and only participants who met all the following requirements were permitted to participate in Experiment 3. That is, participants had to be between 18 - 24 years of age, a US High School Graduate, and have normal to corrected vision. Another concern about recruiting from this platform is the potential for "bots" and fake responses. To control for this, attention checks were included in the post-task questionnaire, which probed participants' attentiveness and was used to filter out nonsensical and low-quality responses.

Another limitation in Experiment 3 is the type of strategy participants used. Participants underwent an implicit learning task, where optimal performance depended upon learning to integrate three different features together. This is typically thought of as an implicit strategy. However, when participants were probed about their decision-making strategies and the types of strategies used, 10.7% of participants reported attempting to memorize the stimuli. This type of recall may be considered more of an explicit strategy, as opposed to an implicit strategy. Additionally, 11.1% of all participants in the uncertainty monitoring condition reported using some form of a memorization technique during the task. Thus, it is possible that participants may have used the uncertain response option when their explicit strategies did not work. This was also observed in other studies investigating uncertainty monitoring during implicit category learning tasks (Paul et al., 2011). Participants may use explicit strategies to categorize stimuli during implicit tasks and use uncertain response options to omit stimuli trials that do not align with their explicit rules. With this approach, participants were still able to maintain a level of accuracy despite using the non-optimal strategy. Considering that prior research has shown that participants may discover creative ways to utilize uncertain response options, it is possible that participants in the present dissertation did so as well.

Lastly, a potential limitation in all three experiments is the use of 10 second "timeouts" when participants made incorrect categorical responses. These timeouts delayed the start of the next task trial and were meant to motivate participants to learn during the task and make correct responses. Participants did not receive timeouts if they selected the "uncertain" response option, however. Thus, it is possible that some participants in the uncertainty monitoring conditions may have used the uncertain response option to skip trials, and to reduce the amount of delay and complete the task faster. Although the data on participants' uncertainty response rates were examined for excessive use and potential outliers, it remains possible that the uncertain response option was used outside of its intended purpose.

General Experiment Conclusions

Taken altogether, the findings in the present dissertation contribute to the fields of cognition and education. The most compelling and consistent finding was the general benefit of uncertainty monitoring on performance. This was observed in Experiment 1, replicated in

Experiment 2, and marginally replicated in Experiment 3 using a new task to study a different type of learning.

Findings from these experiments have important implications for education and cognition research as they demonstrated that metacognitive processes and learning may be enhanced by providing an option to monitor and report uncertainty. Previously, metacognitive skills have primarily been taught using lengthy practices such as reading passages, comprehension monitoring assignments, and self-evaluation questionnaires, all of which may span across an academic semester (i.e., approximately 4 months) (Dang, Chiang, Brown, & McDonald, 2018). While incremental progress may be made using these methods, providing students with the option to report uncertainty allows them to receive immediate clarification, and addresses errors and uncertainty in real-time. This may prevent the perpetuation of misconceptions, and potentially minimize educational consequences such as poor test performance.

Understanding the factors that promote learning and transfer of knowledge is crucial as many real-world skills depend upon one's ability to monitor the quality and reliability of responses. This dissertation investigated an understudied area of cognition and education research, and combined category learning approaches to study uncertainty monitoring within the context of education. More research is necessary, however, to understand the extent to which uncertainty monitoring can support performance.

Future research should expand on the present work by further investigating the effect of uncertainty monitoring during learning of other concepts and categories. This could include classroom concepts from various disciplines. In fact, cognitive theories and training methods have been used to enhance teaching of natural science concepts (Nosofsky & McDaniel, 2019;

Speirs et al., under review). To my knowledge, however, the impact of uncertainty monitoring on different types of learning in education remains relatively underexplored.

Findings from this dissertation could be used to inform instructional designs and training approaches that aim to address uncertainty and learning difficulties. This could entail presenting learners with questions that require them to reflect on their knowledge and understanding of the subject matter, as well as providing them with opportunities to test their knowledge, and report when they are uncertain or don’t know the answer in order to receive immediate feedback. The present dissertation research adds to the growing body of literature on cognitive learning theory in education, and calls for more collaborative research between cognitive science and education researchers to improve teaching and learning.

REFERENCES

Ainsworth, S., & Burcham, S. (2007). The impact of text coherence on learning by self-explanation. *Learning and instruction*, *17*(3), 286-303.

Aron, A. R., Robbins, T. W., & Poldrack, R. A. (2004). Inhibition and the right inferior frontal cortex. *Trends in cognitive sciences*, *8*(4), 170-177.

Ashby, F. G. (1992). Multidimensional models of categorization. In F. G. Ashby (Ed.), Multidimensional models of perception and cognition (pp. 449–483). Lawrence Erlbaum Associates, Inc.

Ashby, F. G., Alfonso-Reese, L. A., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological review*, *105*(3), 442-481.

Ashby, F. G., Maddox, W. T., & Bohil, C. J. (2002). Observational versus feedback training in rule-based and information-integration category learning. *Memory & cognition*, *30*(5), 666-677.

Ashdown, J., & Simic, O. (2000). Is early literacy intervention effective for English language Learners? Evidence from Reading Recovery. *Literacy, Teaching and Learning*, *5*(1), 27-42.

Bachman, L., & Bachman, C. (2011). A study of classroom response system clickers: Increasing student engagement and performance in a large undergraduate lecture class on architectural research. *Journal of Interactive Learning Research*, *22*(1), 5-21.

Bangert-Drowns, R. L., Kulik, C. L. C., Kulik, J. A., & Morgan, M. (1991). The instructional effect of feedback in test-like events. *Review of educational research*, *61*(2), 213-238.

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn? A taxonomy for far transfer. *Psychological bulletin*, *128*(4), 612-637.

Beatty, I. D. (2005). Transforming student learning with classroom communication systems. *arXiv preprint physics/0508129*.

Behrens, T. E., Woolrich, M. W., Walton, M. E., & Rushworth, M. F. (2007). Learning the value of information in an uncertain world. *Nature neuroscience, 10*(9), 1214-1221.

Berger, C. R., & Calabrese, R. J. (1974). Some explorations in initial interaction and beyond: Toward a developmental theory of interpersonal communication. *Human communication research*, *1*(2), 99-112.

Bielaczyc, K., Pirolli, P. L., & Brown, A. L. (1995). Training in self-explanation and self-regulation strategies: Investigating the effects of knowledge acquisition activities on problem solving. *Cognition and instruction*, *13*(2), 221-252.

Boud, D., & Falchikov, N. (1989). Quantitative studies of student self-assessment in higher education: A critical analysis of findings. *Higher education*, *18*(5), 529-549.

Brinck, I., & Liljenfors, R. (2013). The developmental origin of metacognition. *Infant and Child Development*, *22*(1), 85-101.

Bransford, J. D., & Schwartz, D. L. (1999). Chapter 3: Rethinking transfer: A simple proposal with multiple implications. *Review of research in education*, *24*(1), 61-100.

Braunlich, K., & Seger, C. A. (2016). Categorical evidence, confidence, and urgency during probabilistic categorization. *Neuroimage*, *125*, 941-952.

Brophy, J. E. (1979). Teacher Behavior and Its Effects. *Journal of Educational Leadership,* 71, 733-750.

Brown, A. L. (1977). Knowing When, Where, and How to Remember: A Problem of Metacognition. Technical Report, 47.

Brown, A. L., & DeLoache, J. S. (1978). Skills, plans, and self-regulation. *Children's thinking: What develops*, *2*.

Brown, R., & McNeill, D. (1966). The "tip of the tongue" phenomenon. *Journal of verbal learning and verbal behavior*, *5*(4), 325-337.

Bruner, J. (1973). The relevance of education. WW Norton & Company.

Butler, A. C., Godbole, N., & Marsh, E. J. (2013). Explanation feedback is better than correct answer feedback for promoting transfer of learning. *Journal of Educational Psychology*, *105*(2), 290.

Cain, J., Black, E. P., & Rohr, J. (2009). An audience response System strategy to improve student motivation, attention, and feedback. *American Journal of Pharmaceutical Education,* 73(2): 1–7.

Caleon, I. S., & Subramaniam, R. (2010). Do students know what they know and what they don't know? Using a four-tier diagnostic test to assess the nature of students' alternative conceptions. *Research in Science Education*, *40*(3), 313-337.

Callender, A. A., Franco-Watkins, A. M., & Roberts, A. S. (2016). Improving metacognition in the classroom through instruction, training, and feedback. *Metacognition and learning*, *11*(2), 215-235.

Carvalho, P. F., & Goldstone, R. L. (2015). The benefits of interleaved and blocked study: Different tasks benefit from different schedules of study. *Psychonomic bulletin & review*, *22*(1), 281-288.

Cecilio-Fernandes, D., Kerdijk, W., Jaarsma, A. D. C., & Tio, R. A. (2016). Development of cognitive processing and judgments of knowledge in medical students: analysis of progress test results. *Medical teacher*, *38*(11), 1125-1129.

Chi, M. T., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive science*, *13*(2), 145-182.

Chi, M. T., De Leeuw, N., Chiu, M. H., & LaVancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive science*, *18*(3), 439-477.

Chowdhury, S., Gibb, F., & Landoni, M. (2011). Uncertainty in information seeking and retrieval: A study in an academic environment. *Information Processing & Management*, *47*(2), 157-175.

Coutinho, M. V., Redford, J. S., Church, B. A., Zakrzewski, A. C., Couchman, J. J., & Smith, J. D. (2015). The interplay between uncertainty monitoring and working memory: Can metacognition become automatic?. Memory & Cognition, 43(7), 990-1006.

Dienes, Z., & Berry, D. (1997). Implicit learning: Below the subjective threshold. Psychonomic bulletin & review, 4(1), 3-23.

Dienes, Z., & Perner, J. (2002). A theory of the implicit nature of implicit learning. *Implicit learning and consciousness,* 68-92.

Dienes, Z., & Seth, A. (2009). Gambling on the unconscious: A comparison of wagering and Confidence ratings as measures of awareness in an artificial grammar task. *Consciousness and Cognition, 19*(2), 674-681.

Dentakos, S., Saoud, W., Ackerman, R., & Toplak, M. E. (2019). Does domain matter? Monitoring accuracy across domains. *Metacognition and Learning*, *14*(3), 413-436.

Detterman, D. K., & Sternberg, R. J. (Eds.). (1993). Transfer on trial: Intelligence, cognition, and instruction. Ablex Publishing.

Ell, S. W., Smith, D. B., Peralta, G., & Hélie, S. (2017). The impact of category structure and training methodology on learning and generalizing within-category representations. *Attention, Perception, & Psychophysics*, *79*(6), 1777-1794.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The quarterly journal of economics*, 643-669.

Falchikov, N., & Boud, D. (1989). Student self-assessment in higher education: A meta analysis. *Review of educational research*, *59*(4), 395-430.

Fazio, L. K., Huelser, B. J., Johnson, A., & Marsh, E. J. (2010). Receiving right/wrong feedback: Consequences for learning. *Memory*, 18(3), 335-350.

Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. *American psychologist*, *34*(10), 906-911.

Gentner, D., & Smith, L. A. (2013). Analogical learning and reasoning. *The Oxford handbook of cognitive psychology*, 668-681.

Gersten, R., Jordan, N. C., & Flojo, J. R. (2005). Early identification and interventions for students with mathematics difficulties. *Journal of learning disabilities*, *38*(4), 293-304.

Gick, M. L., & Holyoak, K. J. (1987). The cognitive basis of knowledge transfer. In *Transfer of learning* (pp. 9-46). Academic Press.

Goldstone, R. L., Kersten, A., & Carvalho, P. F. (2018). Categorization and concepts. *Stevens' Handbook of Experimental Psychology and Cognitive Neuroscience*, *3*, 1-43.

Goldwater, M. B., & Schalk, L. (2016). Relational categories as a bridge between cognitive and educational research. *Psychological Bulletin*, *142*(7), 729-757.

Granberg, C. (2016). Discovering and addressing errors during mathematics problem-solving—A productive struggle?. *The Journal of Mathematical Behavior*, *42*, 33-48.

Greenwood, P. M. (2000). The frontal aging hypothesis evaluated. *Journal of the International Neuropsychological Society*, *6*(6), 705-726.

Grieve, S. M., Williams, L. M., Paul, R. H., Clark, C. R., & Gordon, E. (2007). Cognitive aging, executive function, and fractional anisotropy: a diffusion tensor MR imaging study. *American Journal of Neuroradiology, 28*(2), 226-235.

Hacker, D. J., Bol, L., Horgan, D. D., & Rakow, E. A. (2000). Test prediction and performance in a classroom context. *Journal of Educational Psychology,* 92, 160 –170.

Hambrick, D. Z. (2003). Why are some people more knowledgeable than others? A longitudinal study of knowledge acquisition. *Memory & cognition*, *31*(6), 902-917.

Hambrick, D. Z., & Meinz, E. J. (2011). Limits on the predictive power of domain-specific experience and knowledge in skilled performance. *Current Directions in Psychological Science*, *20*(5), 275-279.

Händel, M., & Fritzsche, E. S. (2015). Students' confidence in their performance judgements: A comparison of different response scales. *Educational Psychology*, *35*(3), 377-395.

Hart, J. T. (1965). Memory and the feeling-of-knowing experience. *Journal of educational psychology*, *56*(4), 208.

Heath, C., & Tversky, A. (1991). Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of risk and uncertainty, 4*(1), 5-28.

Holyoak, K. J. (2012). Analogy and relational reasoning. *The Oxford handbook of thinking and reasoning*, 234-259.

Isaacson, R., & Fujita, F. (2006). Metacognitive knowledge monitoring and self-regulated learning. *Journal of the Scholarship of Teaching and Learning*, 39-55.

Jacobs, J. E., & Paris, S. G. (1987). Children's metacognition about reading: Issues in definition, measurement, and instruction. *Educational psychologist*, *22*(3-4), 255-278.

Kahneman, D., Slovic, S. P., Slovic, P., & Tversky, A. (Eds.). (1982). Judgment under uncertainty: Heuristics and biases. Cambridge university press.

Kelley, C. M., & Jacoby, L. L. (1996). Adult egocentrism: Subjective experience versus analytic bases for judgment. *Journal of Memory and language, 35*(2), 157-175.

Kikyo, H., & Miyashita, Y. (2004). Temporal lobe activations of “feeling-of-knowing” induced by face-name associations. *Neuroimage*, *23*(4), 1348-1357.

Kikyo, H., Ohki, K., & Miyashita, Y. (2002). Neural correlates for feeling-of-knowing: an fMRI parametric analysis. *Neuron*, *36*(1), 177-186.

King, A. (1994). Guiding knowledge construction in the classroom: Effects of teaching children how to question and how to explain. *American educational research journal*, *31*(2), 338-368.

Koedinger, K. R., & Roll, I. (2012). Learning to think: Cognitive mechanisms of knowledge transfer. *The Oxford handbook of thinking and reasoning*, 789-806.

Koriat, A. (1997). Monitoring one's own knowledge during study: A cue-utilization approach to judgments of learning. *Journal of experimental psychology: General*, *126*(4), 349-370.

Koriat, A., & Bjork, R. A. (2005). Illusions of competence in monitoring one's knowledge during study. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(2), 187-194.

Koriat, A., Nussinson, R., Bless, H., & Shaked, N. (2008). Information-based and experience-based metacognitive judgments: Evidence from subjective confidence. *A handbook of memory and metamemory*, 117-136.

Kornell, N., & Metcalfe, J. (2006). Study efficacy and the region of proximal learning framework. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*(3), 609-622.

Kulhavy, R. W., & Stock, W. A. (1989). Feedback in written instruction: The place of response certitude. *Educational psychology review*, *1*(4), 279-308.

Kuhlthau, C. C. (1993). A principle of uncertainty for information seeking. *Journal of documentation, 49*(4), 339-355.

Kurtz, K. J., Boukrina, O., & Gentner, D. (2013). Comparison promotes learning and transfer of relational categories. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *39*(4), 1303-1310.

Kurtz, K. J., Levering, K. R., Stanton, R. D., Romero, J., & Morris, S. N. (2013). Human learning of elemental category structures: Revising the classic result of Shepard, Hovland, and Jenkins (1961). *Journal of Experimental Psychology: Learning, Memory, and Cognition, 39*(2), 552–572.

Labuhn, A. S., Zimmerman, B. J., & Hasselhorn, M. (2010). Enhancing students' self-regulation and mathematics performance: The influence of feedback and self-evaluative standards. *Metacognition and learning*, *5*(2), 173-194.

Leader, L. F. (1999). *Effects of adjunct questions, self-explanation, and prior knowledge on learning from expository text* (pp. 1-140). Arizona State University.

Lee, S. W., Chung, B. D., Bang, Y. S., & Bae, S. W. (2014). Analysis of Uncertainty Quantification Method by Comparing Monte-Carlo Method and Wilks' Formula. *Nuclear engineering and Technology, 46*(4), 481-488.

Lewandowsky, S. (2011). Working memory capacity and categorization: Individual differences and modeling. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37*(3), 720–738.

Love, B. C. (2002). Comparing supervised and unsupervised category learning. *Psychonomic bulletin & review, 9*(4), 829-835.

Lundeberg, M. A., Fox, P. W., & Punćcohaŕ, J. (1994). Highly confident but wrong: Gender differences and similarities in confidence judgments. *Journal of educational psychology, 86*(1), 114-121.

Maddox, W. T., & Ashby, F. G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & psychophysics, 53*(1), 49-70.

Maddox, W. T., Ashby, F. G., & Bohil, C. J. (2003). Delayed feedback effects on rule-based and information-integration category learning. *Journal of experimental psychology: learning, memory, and cognition*, *29*(4), 650-662.

Maril, A., Simons, J. S., Mitchell, J. P., Schwartz, B. L., & Schacter, D. L. (2003). Feeling-of-knowing in episodic memory: an event-related fMRI study. *Neuroimage*, *18*(4), 827-836.

McCormick, C. B. (2003). Metacognition and learning. *Handbook of psychology*, 79-102.

Medin, D. L., & Schaffer, M. M. (1978). Context theory of classification learning. *Psychological review*, *85*(3), 207-238.

Metcalfe, J. (2002). Is study time allocated selectively to a region of proximal learning? *Journal of Experimental Psychology: General*, *131*(3), 349-363.

Metcalfe, J., & Finn, B. (2008). Evidence that judgments of learning are causally related to study choice. *Psychonomic Bulletin & Review*, *15*(1), 174-179.

Miller, T. M., & Geraci, L. (2011). Training metacognition in the classroom: The influence of incentives and feedback on exam predictions. *Metacognition and Learning, 6*(3), 303-314.

Minda, J. P., Desroches, A. S., & Church, B. A. (2008). Learning rule-described and non-rule-described categories: A comparison of children and adults. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*(6), 1518–1533.

Miyatsu, T., Gouravajhala, R., Nosofsky, R. M., & McDaniel, M. A. (2019). Feature highlighting enhances learning of a complex natural-science category. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *45*(1), 1-16.

Nassar, M. R., McGuire, J. T., Ritz, H., & Kable, J. W. (2019). Dissociable forms of uncertainty-driven representational change across the human brain. *Journal of Neuroscience*, *39*(9), 1688-1698.

Nietfeld, J. L., Cao, L., & Osborne, J. W. (2005). Metacognitive monitoring accuracy and students performance in the postsecondary classroom. *The Journal of Experimental Education*, 74(1), 7–28.

Nietfeld, J. L., Cao, L., & Osborne, J. W. (2006). The effect of distributed monitoring exercises and feedback on performance, monitoring accuracy, and self-efficacy. *Metacognition and Learning*, *1*(2), 159-179.

Nelson, T. O., & Narens, L. (1990). Metamemory: A theoretical framework and new findings. In *Psychology of learning and motivation* (Vol. 26, pp. 125-173). Academic Press.

Nelson, T. O., Stuart, R. B., Howard, C., & Crowley, M. (1999). Metacognition and clinical psychology: A preliminary framework for research and practice. *Clinical Psychology & Psychotherapy: An International Journal of Theory & Practice*, *6*(2), 73-79.

Nosofsky, R. M. (1986). Attention, similarity, and the identification–categorization relationship. *Journal of experimental psychology: General*, *115*(1), 39-57.

Nosofsky, R. M., & McDaniel, M. A. (2019). Recommendations from cognitive psychology for enhancing the teaching of natural-science categories. *Policy Insights from the Behavioral and Brain Sciences*, *6*(1), 21-28.

Nosofsky, R. M., Palmeri, T. J., & McKinley, S. C. (1994). Rule-plus-exception model of classification learning. *Psychological Review, 101*(1), 53–79.

Nosofsky, R. M., Sanders, C. A., Meagher, B. J., & Douglas, B. J. (2018). Toward the development of a feature-space representation for a complex natural category domain. *Behavior Research Methods*, *50*(2), 530-556.

O'Dwyer, A., & Childs, P. (2014). Organic chemistry in action! Developing an intervention program for introductory organic chemistry to improve learners' understanding, interest, and attitudes. *Journal of Chemical Education*, *91*(7), 987-993.

O'Reilly, T., Symons, S., & MacLatchy-Gaudet, H. (1998). A comparison of self-explanation and elaborative interrogation. *Contemporary Educational Psychology*, *23*(4), 434-445.

Paris, S. G., Wasik, B. A., & Van der Westhuizen, G. (1988). Meta-metacognition: A review of research on metacognition and reading. In *National Reading Conference Yearbook*. National Reading Conference.

Paris, S. G., & Winograd, P. (1990). How metacognition can promote academic learning and instruction. *Dimensions of thinking and cognitive instruction*, *1*, 15-51.

Pashler, H., Cepeda, N. J., Wixted, J. T., & Rohrer, D. (2005). When does feedback facilitate learning of words?. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(1), 3-8.

Paul, E. J., Boomer, J., Smith, J. D., & Ashby, F. G. (2011). Information–integration category learning and the human uncertainty response. *Memory & cognition*, *39*(3), 536-554.

Persaud, N., McLeod, P., & Cowey, A. (2007). Post-decision wagering objectively measures awareness. *Nature neuroscience*, *10*(2), 257-261.

Putnam, A. L., & Roediger III, H. L. (2018). Education and Memory: Seven Ways the Science of Memory Can Improve Classroom Learning. *Stevens' Handbook of Experimental Psychology and Cognitive Neuroscience*, *1*, 1-45.

Reber, P. J., Gitelman, D. R., Parrish, T. B., & Mesulam, M. M. (2003). Dissociating explicit and implicit category knowledge with fMRI. *Journal of cognitive neuroscience, 15*(4), 574-583.

Reder, L. M. (1987). Strategy selection in question answering. *Cognitive psychology*, *19*(1), 90-138.

Reder, L. M., & Schunn, C. D. (1996). Metacognition does not imply awareness: Strategy choice is governed by implicit learning and memory. In *Implicit memory and metacognition*, 57-90.

Regan, A., Childs, P., & Hayes, S. (2011). The use of an intervention programme to improve undergraduate students' chemical knowledge and address their misconceptions. *Chemistry Education Research and Practice*, *12*(2), 219-227.

Renkl, A. (2002). Worked-out examples: Instructional explanations support learning by self-explanations. *Learning and instruction*, *12*(5), 529-556.

Renkl, A., Stark, R., Gruber, H., & Mandl, H. (1998). Learning from worked-out examples: The effects of example variability and elicited self-explanations. *Contemporary educational psychology*, *23*(1), 90-108.

Renner, C. H., & Renner, M. J. (2001). But I thought I knew that: Using confidence estimation as a debiasing technique to improve classroom performance. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition*, *15*(1), 23-32.

Rickey, D., & Stacy, A. M. (2000). The role of metacognition in learning chemistry. *Journal of chemical education, 77*(7), 915-920.

Rittle-Johnson, B., Star, J. R., & Durkin, K. (2009). The importance of prior knowledge when comparing examples: Influences on conceptual and procedural knowledge of equation solving. *Journal of Educational Psychology*, *101*(4), 836-852.

Rosenthal, D. (2000). Consciousness and metacognition. In Metarepresentation: Proceedings of the tenth Vancouver cognitive science conference (pp. 265-295). New York: Oxford University Press.

Saetrevik, B., Reber, R., & Sannum, P. (2006). The utility of implicit learning in the teaching of rules. *Learning and Instruction*, *16*(4), 363-373.

Schacter, D. L. (1987). Implicit memory: History and current status. *Journal of experimental psychology: learning, memory, and cognition, 13*(3), 501-518.

Schneider, W., Korkel, J., & Weinert, F. E. (1989). Domain-specific knowledge and memory performance: A comparison of high-and low-aptitude children. *Journal of educational psychology*, *81*(3), 306-312.

Schoenherr, J. R., & Lacroix, G. L. (2020). Performance monitoring during categorization with and without prior knowledge: A comparison of confidence calibration indices with the certainty criterion. *Canadian Journal of Experimental Psychology, 74*(4), 302–315.

Schooler, C. (1989). Social structure effects and experimental situations: Mutual lessons of cognitive and social science. *Social structure and aging: Psychological processes*, 129-147.

Schraw, G. (1998). Promoting general metacognitive awareness. *Instructional science*, *26*(1-2), 113-125.

Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary educational psychology*, *19*(4), 460-475.

Schraw, G., & Moshman, D. (1995). Metacognitive theories. *Educational psychology review*, *7*(4), 351-371.

Schwartz, B. L. (2008). Working memory load differentially affects tip-of-the-tongue states and feeling-of-knowing judgments. *Memory & Cognition*, *36*(1), 9-19.

Seger, C. A., Braunlich, K., Wehe, H. S., & Liu, Z. (2015). Generalization in category learning: the roles of representational and decisional uncertainty. *Journal of Neuroscience*, *35*(23), 8802-8812.

Seger, C. A., & Miller, E. K. (2010). Category learning in the brain. *Annual review of neuroscience*, *33*, 203-219.

Seger, C. A., & Peterson, E. J. (2013). Categorization= decision making + generalization. *Neuroscience & Biobehavioral Reviews*, *37*(7), 1187-1200.

Serra, M. J., & Metcalfe, J. (2009). Effective implementation of metacognition. In *Handbook of metacognition in education* (pp. 290-310). Routledge.

Shepard, R. N., Hovland, C. I., & Jenkins, H. M. (1961). Learning and memorization of classifications. *Psychological monographs: General and applied, 75*(13), 1-42.

Sherry, D. F., & Schacter, D. L. (1987). The evolution of multiple memory systems. *Psychological review, 94*(4), 439.

Smith, J. D., Crossley, M. J., Boomer, J., Church, B. A., Beran, M. J., & Ashby, F. G. (2012). Implicit and explicit category learning by capuchin monkeys (Cebus apella). *Journal of Comparative Psychology, 126*(3), 294-304.

Smith, J. D., & Washburn, D. A. (2005). Uncertainty monitoring and metacognition by animals. *Current Directions in Psychological Science*, *14*(1), 19-24.

Smits, M. H., Boon, J., Sluijsmans, D. M., & Van Gog, T. (2008). Content and timing of feedback in a web-based learning environment: effects on learning as a function of prior knowledge. *Interactive Learning Environments*, *16*(2), 183-193.

Smith, J. D., Coutinho, M. V., Church, B. A., & Beran, M. J. (2013). Executive-attentional uncertainty responses by rhesus macaques (Macaca mulatta). *Journal of Experimental Psychology: General*, *142*(2), 458-475.

Smith, J. D., Minda, J. P., & Washburn, D. A. (2004). Category Learning in Rhesus Monkeys: A Study of the Shepard, Hovland, and Jenkins (1961) Tasks. *Journal of Experimental Psychology: General, 133*(3), 398–414.

Speirs, J. C., Leuteritz, R., Le, T., Ell, S. W., & Deng, R. (under review). Investigating the efficacy of attending to reflexive cognitive processes in the context of Newton's second law. *Physical review letters.*

Sperling, R. A., Howard, B. C., Staley, R., & DuBois, N. (2004). Metacognition and self-regulated learning constructs. *Educational research and evaluation*, *10*(2), 117-139.

Squire, L. R. (1987). Memory and brain. Oxford University Press.

Squire, L. R. (2004). Memory systems of the brain: a brief history and current perspective. *Neurobiology of learning and memory*, *82*(3), 171-177.

Squire, L. R., & Schacter, D. L. (2002). Neuropsychology of memory (3rd ed.). The Guilford Press.

Squire, L. R., & Wixted, J. T. (2011). The cognitive neuroscience of human memory since HM. *Annual review of neuroscience*, *34*, 259-288.

Stieff, M. (2011). Improving representational competence using molecular simulations embedded in inquiry activities. *Journal of research in science teaching*, *48*(10), 1137-1158.

Tulving, E. (1991). Concepts of human memory. Memory: Organization and locus of change, 3-32.

Tulving, E., & Madigan, S. A. (1970). Memory and verbal learning. *Annual Review of Psychology, 21*, 437–484.

Tversky, A., & Fox, C. R. (1995). Weighing risk and uncertainty. *Psychological review*, *102*(2), 269-283.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124-1131.

Tversky, A., & Kahneman, D. (1996). On the reality of cognitive illusions. *Psychological Review*, *103*(3), 582-591.

Vaidya, S. R. (1999). Metacognitive learning strategies for students with learning disabilities. *Education*, *120*(1), 186-186.

Veenman, M. V. (2015). Metacognition. *Handbook of individual differences in reading*, 44-58.

Veenman, M. V., Van Hout-Wolters, B. H., & Afflerbach, P. (2006). Metacognition and learning: Conceptual and methodological considerations. *Metacognition and learning*, *1*(1), 3-14.

Wagner, A. D., Maril, A., Bjork, R. A., & Schacter, D. L. (2001). Prefrontal contributions to executive control: fMRI evidence for functional distinctions within lateral prefrontal cortex. *Neuroimage*, *14*(6), 1337-1347.

Waldron, E. M., & Ashby, F. G. (2001). The effects of concurrent task interference on category learning: Evidence for multiple category learning systems. *Psychonomic bulletin & review, 8*(1), 168-176.

Walker, C. H. (1987). Relative importance of domain knowledge and overall aptitude on acquisition of domain-related information. *Cognition and instruction*, *4*(1), 25-42.

Washburn, D. A., Smith, J. D., & Taglialatela, L. A. (2005). Individual differences in metacognitive responsiveness: Cognitive and personality correlates. *The Journal of general psychology*, *132*(4), 446-461.

Webb, S., Newton, J., & Chang, A. (2013). Incidental learning of collocation. *Language Learning*, *63*(1), 91-120.

Wong, R. M., Lawson, M. J., & Keeves, J. (2002). The effects of self-explanation training on students' problem solving in high-school mathematics. *Learning and Instruction*, *12*(2), 233-262.

APPENDICES

Appendix A.

Post-Task Questionnaire for Experiment 1

Assessing knowledge of Acidity and Basicity

How would you rate your knowledge of the concept of **ACIDITY** before participating in this study? (e.g., 1 = Very Low to 5 = Very High) _______

How would you rate your knowledge of the concept of **ACIDITY** now? (e.g., 1 = Very Low to 5 = Very High) _______

How would you rate your knowledge of the concept of **BASICITY** before participating in this study? (e.g., 1 = Very Low to 5 = Very High) _______

How would you rate your knowledge of the concept of **BASICITY** now? (e.g., 1 = Very Low to 5 = Very High) _______

Please list all the color(s) that correspond with the **ACIDIC** category: ______________

Please list all the color(s) that correspond with the **BASIC** category: _______________

Attention Check

If you are paying attention, please select "Other" (e.g., Yes, No, Other) _______

Probing Decision-Making Strategies

Did you use any strategies or rules to make your decisions? (Yes or No)

If yes, please describe them: ____

Probing Confidence

How confident were you in your answers during the **TRAINING** phase? (e.g., 1 = Not at all Confident to 7 = Extremely Confident) _______

How confident were you in your answers during the **TEST** phase? (e.g., 1 = Not at all Confident to 7 = Extremely Confident) _______

Appendix B.

Post-Task Questionnaire for Experiment 2

Assessing knowledge of Acidity and Basicity

How would you rate your knowledge of the concept of **ACIDITY** before participating in this study? (e.g., 1 = Very low to 5 = Very High) _______

How would you rate your knowledge of the concept of **ACIDITY** now? (e.g., 1 = Very Low to 5 = Very High) _______

How would you rate your knowledge of the concept of **BASICITY** before participating in this study? (e.g., 1 = Very Low to 5 = Very High) _______

How would you rate your knowledge of the concept of **BASICITY** now? (e.g., 1 = Very Low to 5 = Very High) _______

Please list all the color(s) that correspond with the **ACIDIC** category: ______________

Please list all the color(s) that correspond with the **BASIC** category: _______________

Attention Check

If you are paying attention, please select "Other" (e.g., Yes, No, Other) _______

Probing Decision-Making Strategies

Did you use any strategies or rules to make your decisions? (Yes or No)

If yes, please describe them: __________________________________

Assessing Calibration Accuracy

On a scale from 0 to 100 (e.g., 0 = poor, 100 = excellent), how do you think you scored during **TRAINING** phase? _______

How confident are you in this performance rating? (e.g., 1 = Not at all Confident to 7 = Extremely Confident) _______

On a scale from 0 to 100 (e.g., 0 = poor, 100 = excellent), how do you think you scored during **TEST** phase? ________

How confident are you in this performance rating? (e.g., 1 = Not at all Confident to 7 = Extremely Confident) _______

Appendix C.

Post-Task Questionnaire for Experiment 3

Probing Decision-Making Strategies

Did you use any strategies or rules to make your decisions? (Yes or No)

If yes, please describe them: ____________________________________

Did you at any point during the task guess your answers? _______

Attention Check

If you are paying attention, please select "Other" (e.g., Yes, No, Other) _______

Assessing Calibration Accuracy

On a scale from 0 to 100 (e.g., 0 = poor, 100 = excellent), how do you think you scored during **BLOCK 1**? _______

How confident are you in this performance rating? (e.g., 1 = Not at all Confident to 7 = Extremely Confident) _______

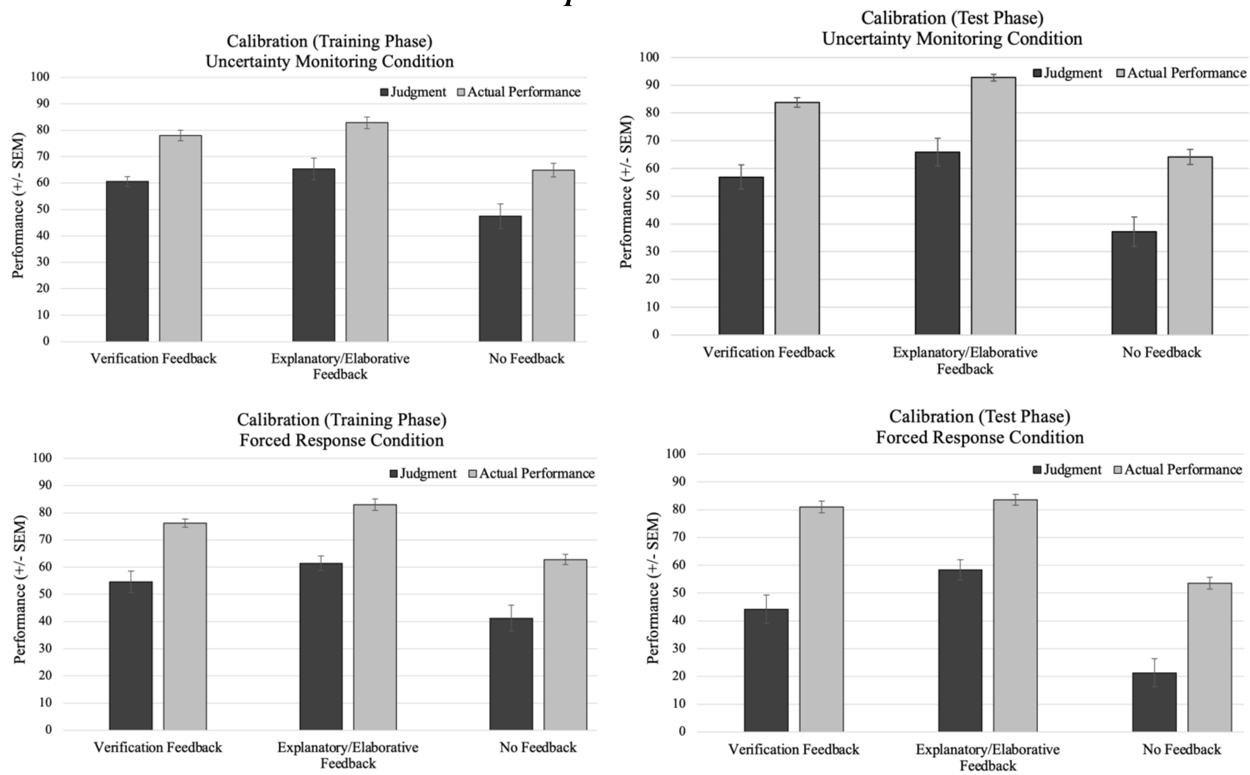
On a scale from 0 to 100 (e.g., 0 = poor, 100 = excellent), how do you think you scored during **BLOCK 2**? _______

How confident are you in this performance rating? (e.g., 1 = Not at all Confident to 7 = Extremely Confident) _______

Appendix D.

Judgment of Performance vs. Actual Performance

Experiment 2B



Experiment 3

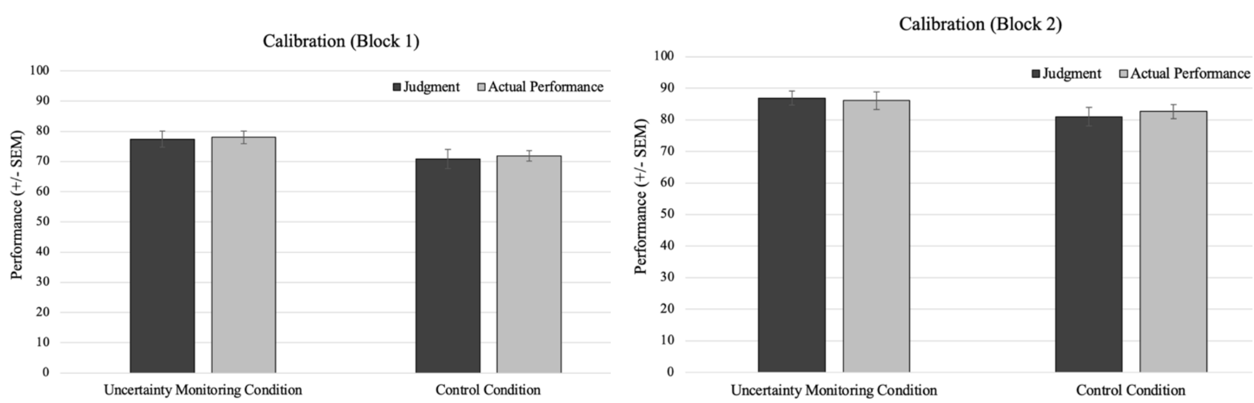


Figure 43. Participants' judgments of performance compared to their actual performance (i.e., calibration). Charts represent calibration by feedback type for (Top row) Uncertainty Monitoring training condition in Experiment 2b, (Middle row) Forced Response training condition in Experiment 2b, and (Bottom row) Calibration between training methods in Experiment 3.

BIOGRAPHY OF THE AUTHOR

Rose Deng was born and raised in Queens, New York. She attended York College of the City University of New York and graduated in 2015 with a Bachelor’s degree in Psychology. After receiving her Doctorate, Rose will be continuing on to a career in data science and analytics. Rose is a candidate for the Doctor of Philosophy degree in Psychology from the University of Maine in December 2022.