Implicit Learning in Science:
Activating and Suppressing Scientific Intuitions to Enhance Conceptual Change

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Dedication

For Ange

Abstract

This dissertation examines the thesis that implicit learning plays a role in learning about scientific phenomena, and subsequently, in conceptual change. Decades of research in learning science demonstrate that a primary challenge of science education is overcoming prior, naïve knowledge of natural phenomena in order to gain scientific understanding. Until recently, a key assumption of this research has been that to develop scientific understanding, learners must abandon their prior scientific intuitions and replace them with scientific concepts. However, a growing body of research shows that scientific intuitions persist, even among science experts. This suggests that naïve intuitions are suppressed, not supplanted, as learners gain scientific understanding. The current study examines two potential roles of *implicit learning* processes in the development of scientific knowledge. First, *implicit learning* is a source of cognitive structures that impede science learning. Second, tasks that engage *implicit learning* processes can be employed to activate and suppress prior intuitions, enhancing the likelihood that scientific concepts are adopted and applied. This second proposal is tested in two experiments that measure training-induced changes in intuitive and conceptual knowledge related to sinking and floating objects in water. In Experiment 1, an implicit learning task was developed to examine whether implicit learning can induce changes in performance on near and far transfer tasks. The results of this experiment provide evidence that implicit learning tasks activate and suppress scientific intuitions. Experiment 2 examined the effects of combining implicit learning with traditional, direct instruction to enhance explicit learning of science concepts. This experiment demonstrates that sequencing implicit learning task before and after direct instruction has different effects on intuitive and conceptual knowledge. Together, these results suggest a novel approach for enhancing learning for conceptual change in science education.

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Overview

Well before reaching the science classroom, children develop knowledge and beliefs about how the world works. These ideas are acquired through everyday experiences starting from infancy (Au, 1994; Hatano & Inagaki, 1994; Piaget, 1976; Spelke, 1990; for review, see Baillargeon, 2002). They are deeply held and resistant to change from formal instruction (Chi, 2005; Chinn & Brewer, 1993; Gregg, Winer, Cottrell, Hedman, Fournier, 2001; Hammer, 1996; McCloskey, 1983; Smith, diSessa, & Roschelle, 1993). In some cases, these ideas are incongruent with scientific understanding. The science education literature refers to these as "intuitive," "alternative," or "naïve" science ideas, concepts, beliefs, or theories, or simply as "scientific misconceptions" (for reviews, see Confrey, 1990; Pfundt & Duit, 1993; West & Pines, 1985). Thus, science education depends on, and is in fact the business of, *conceptual change* – the process by which students' previous, naïve concepts give way to mature scientific understanding (Carey, 1985, 2000; Duit & Treagust, 2003; Posner, Strike, Hewson, & Gertzog, 1982; Strike & Posner, 1992).

Although research on conceptual change has been conducted for several decades (e.g. Chi, 1992, 2008; diSessa, 1988, 1993; Posner et al., 1982; Strike & Posner, 1992; Vosniadou, 1994), there is no consensus on how conceptual change is best achieved through instruction (Lin, Yen, Liang, Chiu, & Guo, 2016; Özdemir & Clark, 2007). Divergence in viewpoints may stem from a lack of clarity about what changes constitute conceptual change (diSessa & Sherin, 1998; Rusanen, 2014; Taber, 2011). For example, some of the changes theorists have suggested that constitute conceptual change include changes in epistemological beliefs (Vosniadou, 1994), ontological categories (Chi, Slotta, & de Leeuw, 1994), arrangement of pieces of knowledge (diSessa, 1993, 2002), or responses to anomalous data (Chinn & Brewer, 1998).

In addition to differing accounts of the changes that occur in conceptual change, few, if any, theories specify the mechanisms by which these changes occur (Clement, 2008). As Rusanen (2014) has argued, an explanation of conceptual change must offer (1) a description of the information processing task, and (2) a sufficiently accurate and detailed description of the cognitive mechanisms responsible for the task of conceptual change. Current theories of conceptual change fail to describe how well-researched psychological constructs such as attention, short- and long-term memory, and executive functions contribute to or constrain the process of conceptual change (Rusanen & Pöyhönen, 2013).

Current conceptual change theories are also limited in their ability to explain non-rational behaviors associated with science learning. One criticism of early accounts of conceptual change was that they assumed *cold cognition* – that students (and scientist) think and learn in overly rational ways. Theorists have argued that this approach ignores the influence from "hot" cognition involving motivational, emotional, and social contextual variables (Pintrich, Marx, Boyle, & Summer, 1993). Meanwhile, psychological research has revealed the prevalence of cognitive biases, which describe conditions and contexts that result in "predictably irrational" thinking and behavior prevalent in human cognition (Tversky & Kahneman, 1974; Ariely, 2010). Further research is needed to explain the irrationality observed in people's thinking that persists after they have been exposed to science concepts.

Another important criticism of the conceptual change involves methodological issues related to researching conceptual change (Taber, 2011). A recent review of the literature found that, of 116 empirical studies on conceptual change between 1982 and 2011, the majority focus on instructional interventions, often including multiple interventions without taking student characteristics into consideration (Lin et al., 2016). These studies may demonstrate whether or not conceptual change interventions are effective; however, they bring little clarity to the question of *why* and *for whom* these techniques work. An empirical challenge for conceptual change research lies in developing techniques to capture the changes that occur during learning (Magnusson, Templin, & Boyle, 1997). Thus, more tools are needed to examine what changes in conceptual change.

This dissertation research attempts to address these issues by exploring the role of *implicit learning* (Reber, 1967, 1989; Seger, 1994; Shanks, 2004) – the acquisition of complex knowledge in the absence of intention or awareness – in the development of scientific knowledge and conceptual change. A central goal of this dissertation is to demonstrate how theory and methods from implicit learning research can be applied to provide insight into the cognitive processes involved in scientific understanding and conceptual change. In the chapters that follow, we develop and test the general hypothesis that implicit learning processes can be leveraged in instructional settings to enhance conceptual change by activating and suppressing prior intuitive knowledge.

A central challenge to conceptual change theory and research is how to effectively characterize, address, and assess students' prior, inaccurate knowledge. Chapter 1 reviews previous approaches to this challenge, discussing prior research in terms of the coherence of misconceptions and the role of student characteristics in conceptual change processes. We then consider recent methodological and theoretical developments that bring into question certain aspects of prior conceptual change accounts. Specifically, this research shows that prior, intuitive beliefs are suppressed, not supplanted, by scientific understanding. This review raises two important questions: (1) From where do scientific intuitions come? and (2) How can instructional interventions enhance the suppression of inaccurate intuitions? These questions are addressed in Chapters 2 and 3, respectively, in terms of theory and research on implicit learning.

Scientific intuitions important for conceptual change may develop through *implicit learning*. In models of conceptual change, unconsciously held conceptual structures–such as ontological categories, epistemological beliefs, or phenomenological primitives–explain why some science concepts are difficult to learn. These conceptual structures may be acquired through experience, without intention or awareness to learn. Research on *implicit learning*—which occurs in the absence of intention and awareness—may offer insights into how scientific intuitions develop and change, as well as methods for examining them. In Chapter 2, implicit learning processes are further discussed as a source of scientific intuitions.

Implicit learning may also be leveraged to make science instruction more effective. Emerging research suggests that learning for conceptual change involves inhibition of previous intuitive ideas. Evidence from reaction time (Babai, Sekal, & Stavy, 2009; Potvin, Masson, Lafortune, & Cyr, 2014; Shtulman & Valcarcel, 2012) and neuroimaging studies (Dunbar, Fugelsang, & Stein, 2007; Foisy, Potvin, Riopel, & Masson, 2015; Masson, Potvin, Riopel, & Foisy, 2014) supports the view that experts engage inhibitory mechanisms when processing scientific information. Further, there is evidence that activating inhibitory control mechanisms can hinder intuitive reasoning (Babai, Eidelman, & Stavy, 2012), which may offer valuable opportunities for instructional interventions to promote conceptual change. Research and theory related to the role of inhibitory processes in conceptual change are discussed in Chapter 3.

This dissertation research examines a novel approach for examining intuitive science ideas. Simple judgment tasks, based on implicit learning paradigms, provide empirical evidence that intuitive science ideas influence processing throughout the development of a concept from novice to expert understanding. These tasks also provide opportunities to train learners to suppress intuitive ideas by activating inhibitory processes. In Experiment 1, presented in Chapter 4, learners are presented with a task designed to activate intuitive ideas related to sinking and floating objects (i.e. “heavier/larger objects sink,” “hollow objects float," "holes make objects sink"). The accuracy and reaction time measures are compared to conceptual knowledge assessment measures to examine the relationship between intuitive and scientific knowledge. Comparison of reaction times and accuracy across items that are congruent or incongruent with intuitive ideas support the claim that implicit learning can influence intuitive knowledge. This effect was influenced by degree to which task directions guided participants to either explicitly test hypotheses or to make implicit judgments based on intuitions.

Experiment 2 provides further exploration of how implicit learning tasks can be used to impact conceptual change. Implicit training tasks may enhance learning for conceptual change by providing opportunities to apply concepts acquired by direct instruction. That is, conceptual change occurs when explicit learning precedes implicit learning by reinforcing explicitly learned rules. On the other hand, conceptual change may be enhanced when implicit learning tasks prepare learners for direct instruction. In this experiment, participants completed implicit learning tasks and received direct instruction via text in varying sequences. Conceptual knowledge of sinking and floating objects was then assessed through traditional assessment items, as well as implicit judgment tasks. Although direct instruction led to greater gains in conceptual knowledge, as compared to Experiment 1, the effects on intuitive knowledge depended on whether implicit learning tasks occurred before or after direct instruction. The results of Experiment 2 are further discussed in Chapter 5.

The results of these experiments provide insights into how we understand the nature of the scientific knowledge that students bring to the classroom from informal learning environments, as well as directions for designing instruction to address and change those intuitions. This work builds on emerging research that shows that inhibition plays an important role in conceptual change, and provides empirical support for models of conceptual change that emphasize the prevalence of scientific concepts. The implications and limitations of the experimental results, as well as directions for future research, are further discussed in Chapter 6.

Chapter 1: The Persistence of Scientific Intuitions

A central challenge in science education research is explaining how intuitive science ideas give way to scientific understanding – a process referred to as *conceptual change*. Historically, conceptual change research in science education has approached this challenge by (1) cataloging and characterizing the prevalence and nature of common misconceptions; (2) measuring the effects of various student characteristics on conceptual change; and (3) developing and testing instructional interventions for invoking conceptual change among students. In this chapter, I review selected findings from the literature in each of these areas that inform the current research. Then, I discuss recent developments in conceptual change research that inform this dissertation research. I conclude by providing a definition of *scientific intuitions,* informed by conceptual change theory and findings from cognitive science.

A (Brief) History of Conceptual Change Research

The history of conceptual change research in science can be traced back to the late 1970s, when a critical turning point for science education research occurred. Building on the work of Piaget (1976) and constructivist psychologists (e.g. Ausubel, 1968), researchers began reporting about students' rich, yet inaccurate, ideas about scientific phenomena. The early work in this area catalogued the myriad incorrect ideas and explanations about scientific phenomena generated by students; researchers referred to this prior knowledge as "misconceptions," "alternative frameworks," or simply "student ideas" (Driver, Asoko, Leach, Mortimer, & Scott, 1994; Driver & Easley, 1978; Driver, Guesne, & Tiberghien, 1985; Novak, 1977; Nussbaum & Novick, 1982; Pfundt & Duit, 1985; Viennot, 1979). This "first wave of a cognitive approach" (Roth, 2008, p. 31) to understanding students' prior knowledge was no doubt inspired by David

Ausubel's insight that "The most important single factor influencing learning is what the learner already knows" (1968, p. vi, quoted in Duit & Treagust, 1998).

The next important finding made by researchers studying students' naïve science ideas was that this knowledge persists across age levels and in spite of instruction. For example, students demonstrate misconceptions about physics concepts, such as that "motion implies force," across a range of ages and contexts (Clement, 1982; McCloskey, 1983). Similar observations have been made about a variety of scientific concepts, such as astronomy (Vosniadou & Brewer, 1992), sound and light (Mazens & Lautrey, 2003; Reiner, Slotta, Chi, & Resnick, 2000), heat and temperature (Wiser & Carey, 1983), and biology (Babai, Sekal, & Stavy, 2009; Coley & Tanner, 2015). Of particular concern is that intuitive ideas persist despite science instruction directly counteracting misconceptions (Champagne, Gunstone, & Klopfer, 1983; Duit & Treagust, 2003; Eaton, Anderson, & Smith, 1984; Gregg, Winer, Cottrell, Hedman, & Fournier, 2001; Smith, diSessa, & Roschelle, 1993; Tirosh, Stavy, & Cohen, 1998). This prompted researchers to attempt to explain why certain types of prior knowledge are difficult to overcome.

Models of conceptual change

In the early 1980s, Posner, Strike, Hewson, & Gerzog (1982) proposed what has become known as the *classical model* of conceptual change (Vosniadou, 2012). According to this model, conceptual change is initiated by generating *dissatisfaction* with existing conceptions. Subsequently, the learner must find the scientific conceptions presented to be *intelligible* (clear enough to be understood), *plausible* (possibly correct or true), and *fruitful* (productive for solving problems) (Posner et al., 1982). This *classical model* later incorporated the idea of "conceptual ecology" – the cognitive artifacts, epistemic commitments and metaphysical beliefs held by the learner, as well as the milieu of the learner's personal and social goals, attitudes, and motivations (Strike & Posner, 1985; 1992).

This *classical model* described by Posner and colleagues (1982) has been highly influential in science education research and instructional design, particularly in identifying the role of conceptual conflict in conceptual change. However, there are many ways in which this theory falls short of capturing important aspects of conceptual change (Vosniadou, 2012). For example, the *classical* account predicts that a sudden shift in conceptual knowledge should occur when learners move from an old theory to a new one. However, evidence shows that conceptual change tends to be a slow, incremental change among students (Carey, 2000; Mazens & Lautrey, 2003). The *classical* account of conceptual change also did not address the influence of affective, motivational, and social factors during learning (Hitano & Inagaki, 2003; Sinatra & Pintrich, 2003). Further, the classical account was meant to be epistemological, rather than psychological, in nature (Strike & Posner, 1992). Thus, this theory draws primarily from literature in history and philosophy of science and focuses on describing the development of normative, rational beliefs, as opposed to cognitive mechanisms supported by psychological theory.

Soon after the development of the *classical* account of conceptual change in science education, researchers in the field of developmental psychology became interested in how young children develop concepts of scientific phenomena starting from an early age (Carey, 1985; Gopnik, 1996). Like the *classical* accounts of conceptual change, this perspective was heavily influenced by the observed similarities between cognitive development in children and accounts of scientific theory change observed by historians and philosophers of science (Gopnik, 1996). Researchers in this area conducted developmental studies of how children's ideas about various scientific phenomena change over time, in domains such as physical laws that govern objects and substances (e.g.

Au, 1994; Spelke, 1990), biological categories such as *living thing, person, animal, plant,* etc. (e.g. Carey, 1985; Hatano & Inagaki, 1994), and folk psychology (e.g. Gopnik & Wellman, 1992). Because populations of learners in these studies are very young (infant to preschool age) and studies often employ non-verbal assessment methods such as categorization and analysis of looking behaviors.

A common view among developmental psychologists is that children hold 'theory-like' structures that shape their beliefs and observations, and that these theories change over time (Carey, 2000; Gopnik & Wellman, 1992; Gopnik, 1996). These structures are 'theory-like' in that they afford children to engage in cognitive activities similar to scientists, such as prediction, interpretation and explanation of evidence. However, these cognitive structures do not hold the same status as scientific theories in that they do not operate at an explicit, conscious level. Nevertheless, developmental psychologists view conceptual change as involving changes in children's cohesive underlying theoretical framework of the material world. Developmental psychologists have theorized that some knowledge is innate, forming "core knowledge" around which new skills and beliefs are built using the same cognitive devices adults use in science (Gopnik, 2003; Spelke & Kinzler, 2007). However, unlike adult scientists, the abstract, coherent systems of causal entities and rules that make up children's theories are not demonstrated explicitly through language and symbols.

Another prominent theory of conceptual change is the "ontological shift" model (Chi, 1992; Chi, Slotta, & de Leeuw, 1994). This conceptual change theory proposes that some of the difficulties learners have in acquiring scientific concepts arise from the improper characterization of the ontological nature of scientific concepts (Chi, Slotta, & de Leeuw, 1994; Thagard, 1992). A key assumption of this model is that people associate concepts with distinct ontological categories, such as *processes*, *ideas*, and *material substances* (Chi, 1992; Slotta & Chi, 2006). These categories assign different attributes to their members; for example, *substances* take up space while *processes* occur over time. When learning about scientific concepts*,* learners often misapply ontological categories to explain and make predictions about natural phenomena (Reiner, Slotta, Chi, & Resnick, 2000). For example, when describing phenomena related to *force* or *heat*, novices apply characteristics common to *substance*; they might say a force is “all used up” or that heat is a material made of “hot molecules” (Chi, 2013). On the other hand, science experts view these concepts as *emergent processes* – they occur over time, and have causal or non-causal agents. This “ontological shift” model suggests that one way to encourage conceptual change is to make learners aware of categorical mistakes through ontological training (Slotta & Chi, 2006). Although this theory proposes how these cognitive structures influence conceptual change, it does not provide an explanation for how ontological categories and their associated attributes are acquired.

The “framework theory” model of conceptual change also suggests that children have cohesive, well-organized theories are responsible for producing specific beliefs about scientific phenomena (Vosniadou, 1994, 2012). This model claims that children develop explanations and synthetic mental models based on a framework theory composed of their epistemological beliefs, ontological commitments, and the observational evidence available. Thus, conceptual change involves the development of these underlying cognitive structures. For example, children’s epistemological commitments may mature from perceptually-based naïve realism (e.g. “Things are as they appear”) to a more sophisticated scientific epistemology (e.g. “Models can explain phenomena that can’t be seen”). In the “framework theory,” children develop scientifically naïve epistemologies and ontologies before they come to school through their perceptual experiences (Vosniadou, 2012).

Observations from structured interviews of students provide evidence that students combine the ideas they are taught in school with their epistemological and ontological preconceptions gained through everyday experiences. When this occurs, students create synthetic mental models of scientific phenomena (Vosniadou, 2002; Vosniadou & Brewer, 1992). For example, when children are taught that Earth is round, they combine this information with their ontological presuppositions of ‘Earth as an object’ (as opposed to ‘Earth as an astronomical body,’ like the Moon) and the epistemic commitment that ‘things are as they seem’ (i.e. the Earth *looks* flat from everyday experience). This combination of presuppositions and learned ideas results in an idiosyncratic, synthetic mental model of the Earth. In this case students develop a “flattened disc” model of Earth that preserves the view of Earth as an object, combined with the view that the Earth looks flat from a first-person point-of-view.

The conceptual change theories discussed above emphasize a coherent and organized nature of learners’ pre-instructional knowledge. The *knowledge-as-elements* perspective has emerged as a prominent opposing stance in conceptual change literature. Theorists from this perspective object to previous accounts of conceptual change for several reasons (Smith, diSessa, & Roschelle, 1993). First, viewing misconceptions as coherent and wrong implies that they only hinder science learning. This view is incongruent with constructivist views of learning that identify prior knowledge as an important resource for learning. Second, viewing children’s knowledge as theory-like suggests that conceptual change involves a shift from a learner’s current theory to a scientific one. In this process, old theories are abandoned in favor of new, more fruitful theories, in a manner akin to “scientific revolutions” described by Kuhn (1962). However, evidence suggests that conceptual change is a slow, gradual process that occurs over extended periods of time (Caravita & Hallden, 1994; Mazens & Lautrey, 2003). Another criticism includes the overemphasis on generating cognitive conflict. Students often overlook anomalies or explain them away to avoid conflict (Chinn & Brewer, 1993). In order to address these and other concerns, researchers have developed theories that explain misconceptions by taking a more atomic view of science ideas.

According to the *knowledge-in-pieces* view, intuitive science knowledge is composed of multiple, small, independent conceptual elements that interact in an *ad hoc* basis depending on the relevant situation (diSessa, 1988). One of the key proponents of this view, Andrea diSessa, proposed the existence of phenomenological primitives (*p-prims*) – simple, isolated, self-contained pieces of knowledge that come from superficial interpretations of the physical world (diSessa, 1988, 1993; Smith, diSessa, & Roschelle, 1993). *P-prims* are phenomenological in the sense that they arise from our experience of the world; they are primitive in the sense that they are minimal abstractions that are self-evident. For example, the *p-prim* "closer means stronger" arises from everyday experiences with the transfer of heat and light energy: a flame will feel warmer and look brighter as you get closer to it. However, when this productive bit of knowledge is applied to the causes of the seasons on Earth (i.e. "Seasons are caused by Earth being closer to the Sun in summer"), it would appear as a misconception—seasons are not caused by the distance between the Sun and Earth, but by changes in the incidence of sunlight caused by the tilt of Earth's axis. Although *p-prims* have truth value based on everyday experiences, they can also generate misconceptions when inappropriately applied to explain scientific phenomena.

According to the *knowledge-in-pieces* perspective, conceptual change is an evolutionary process by which weakly structured prior ideas (i.e., *p-prims*) become increasingly contextualized and connected to new concepts through addition and reorganization of a network of knowledge elements (Özdemir & Clark, 2007). Thus, conceptual change is a slow, evolutionary process due to the numerous mental manipulations needed to reorganize pieces of knowledge into a cohesive, systematic structure. This model of conceptual change explains the persistence of misconceptions through the fact that *p-prims* do not go away or disappear; they continue to be a part of a reorganized conceptual system. While *p-prims* can lead to inaccurate science beliefs, they remain useful in non-scientific contexts. and because they have been gained through a multitude of experiences, they are difficult to change.

Despite theoretical differences in these models, there is widespread agreement about several aspects of conceptual change. First, learners acquire naïve science knowledge from their everyday experience. Second, science knowledge begins developing early, starting in infancy (Keil, 2011). Third, intuitive knowledge influences how students process information during instruction (Özdemir & Clark, 2007). Fourth, this knowledge is highly resistant to change via instruction (Carey, 2000; Chi, Slotta, & deLeeuw, 1994; diSessa, 1982; Guzzetti, Snyder, Glass, & Gamas, 1993; Özdemir & Clark, 2007; Vosniadou, 1994). Finally, and most relevant for the current research, the conceptual structures that explain difficulties associated with conceptual change (i.e. core knowledge, ontological categories, epistemological beliefs, and *p-prims*) are acquired and exert their influence in an automatic, unconscious, and unintentional manner.

The models of conceptual change described above all propose conceptual structures that make science learning difficult. Further, each of these models suggest that scientific understanding results from changes in these conceptual structures—core knowledge is tested, ontological categories shift, epistemological beliefs mature, and *p-prims* are rearranged. An important missing piece of these models is a psychological account of how these knowledge structures are formed and changed. In Chapter 2, I will describe psychological accounts of *implicit learning*, arguing that these processes are a source of the prior knowledge that influences conceptual change.

Student characteristics that influence conceptual change

Another important theme over the history of conceptual change research is the influence of various student characteristics on conceptual change processes. Over the past 30 years of conceptual change research, commonly-studied student characteristics are gender, grade level, reasoning ability, emotion/motivation, and prior knowledge (Lin, et al., 2016). Other than gender, the two most often studied student characteristics are reasoning ability and emotional/motivational variables. Below, I describe some of the major findings in each of these areas.

Scientific reasoning ability appears to be an important factor in conceptual change processes. As with research on conceptual change, research on scientific reasoning has its roots in Piaget's observations of the development of thinking abilities. According to his well-known theory, children progress through stages of development, reaching the formal operational stage in early adolescence. This stage is characterized by hypothetico-deductive reasoning and abstract thought, which are most closely associated with scientific reasoning (Piaget, 1976). Lawson (1987) developed the Classroom Test of Scientific Reasoning ability to measure students' ability to perform mental operations associated with science concepts. Several of the items on this task are similar to Piagetian tasks used to examine the development of cognitive abilities in young children (e.g., pendulum and balance beam tasks).

Research employing this test suggests that the development of scientific reasoning is correlated with conceptual change. For example, Kwon and Lawson (2000) used a modified version of the scientific reasoning test to examine associated changes in conceptual knowledge about air pressure in students 13 to 17 years old. They concluded that conceptual knowledge acquisition involves the ability to inhibit task-irrelevant information, as well as represent abstract scientific concepts. Their research showed that these abilities increase over the course of adolescence.

Other researchers have employed a similar approach to understanding the relationship between concept learning and reasoning by measuring how individual differences in cognitive ability are related to science knowledge acquisition (Al khawaldeh & Al Olaimat, 2010; Lawson & Thompson, 1988; Liao & She, 2009; Lin et al., 2016). Researchers have hypothesized that ability constructs associated with deliberate control and manipulation of symbols, such as working memory and fluid intelligence, are likely to correlate with science learning. For example, in a review of five studies, Yuan and colleagues (2006) examined the relationship between working memory capacity and science learning tasks (such as science achievement tests and chemistry problem-solving), finding evidence for modest positive correlation.

On the other hand, evidence suggests that general cognitive abilities are a necessary, but not sufficient, driving factor for scientific concept development. In a large-scale study of college students in China and the United States, Bao and collaborators (2009) found that while students demonstrate similar levels of domain-general scientific reasoning ability, Chinese students perform much better than American students on conceptual inventories of physics topics (mechanics, electricity and magnetism). The authors conclude that differences in conceptual knowledge can be accounted for by differences in science instruction across these populations, but that these differences do not affect students' scientific reasoning abilities. An alternative interpretation is that cognitive abilities are not sufficient for the development of conceptual knowledge. Put another way, unlike scientific reasoning abilities, conceptual knowledge is not likely to develop without adequate exposure and effective instruction.

Another line of research has examined the role of emotional and motivational factors in driving conceptual change. In a seminal article, Pintrich, Boyle, & Marx (1993) argued that motivational constructs, such as goals, values, self-efficacy, and control beliefs, are potential mediators of conceptual change.

This argument against a “cold,” overly-rational model of conceptual change has led to a body of work exploring how non-cognitive constructs influence science learning. For example, a recent study showed that for students with high levels of prior misconceptions, having high self-efficacy, confidence and interest can improve the likelihood of conceptual change (Cordova, Sinatra, Jones, Taasoobshirazi, & Lombardi, 2014). This research suggests that a mixture of these motivational and self-belief constructs can modulate the effects of prior knowledge, instructional interventions, and cognitive abilities on conceptual change.

Recent Developments in Conceptual Change

Recent theory and research reveals three important insights regarding the nature of learner’s naïve knowledge. First, naïve knowledge is situated in the task environment (Kloos, Fisher, & Van Orden, 2010; Roth, 2008; Vosniadou, 2007). Second, alternative conceptions are the result of heuristic, rather than logical, reasoning (diSessa & Sherin, 1998; Talanquer, 2009). Third, naïve knowledge structures are suppressed, not supplanted in experts’ knowledge structures (Shtulman & Varcarcel, 2012; Potvin, Masson, Lafortune, & Cyr, 2014). Together, these ideas have important implications for how conceptual change is understood and suggest new approaches to instruction for conceptual change.

Naïve knowledge is situated in the task environment

Early conceptual change theory addressed knowledge from a cognitive perspective; more recently, researchers have shifted toward understanding learning from a situated view (Billett, 1996; Vosniadou, 2007). From a cognitive perspective, knowledge is held in the mind of the individual learner. Learning occurs through an individual’s general abilities and the acquisition of concepts, symbols, and language. The development of these mental skills allows the learner to recognize patterns, solve problems, and explain phenomena. On the other hand, the situated perspective approaches knowledge as “a relation between the individual and a social or physical situation” (Greeno, 1989, p. 1). Rather than an object or thing in the mind, knowledge is an individual’s “potential for situated activity” (Greeno, 1989, p. 1).

Recently, researchers have developed empirical support for a situated view of scientific misconceptions. Knowledge of sinking and floating objects has been shown to be sensitive to task conditions. Kloos, Fisher, & Van Orden (2010) examined how task constraints influenced children and adults’ performance on a density judgment task – predicting whether an object sinks or floats in water. The researchers manipulated the salience of the density variable by presenting objects in pairs where mass, volume, and density dimensions were either confounded or unconfounded with one another. For example, a confounded pair of objects might include a ball with a larger volume, but smaller density, than the other ball. Thus, although this ball is bigger, it is more likely to float. Results of this study showed that task performance on the same object varied based whether or not the pair was confounded on these variables, providing further evidence to question the traditional cognitive view of knowledge as a stable representation in memory.

Even when presumably stable cognitive abilities are taken into account, they may interact with situational task variables. In a study conducted by Wang, Varma, & Varma (2012), participants predicted whether single objects would sink or float in water. Participants’ cognitive abilities were also measured using well-established executive function (EF) ability measures, the Dimensional Change Card Sort (Zelazo, 2006) and Flanker task (Eriksen & Eriksen, 1974). Objects were presented in either a random or structured sequence. In the structured sequence, the number of changes in object characteristics from trial-to-trial was minimized, and sequences were designed to challenge common intuitive beliefs by first presenting objects congruent with intuitive rules about sinking and floating objects (e.g. “heavy objects sink”, “hollow objects float”) followed by objects incongruent with intuitive beliefs. Results from this study showed that, across participants, prediction accuracy was higher and reaction time lower in the structured sequence condition. Further, the sequence conditions interacted with individual differences in executive function (EF) ability (as measured by Dimensional Change Card Sort and Flanker tasks) such that participants with lower EF ability benefitted more from the structured sequence. That is, variation in cognitive abilities may hinder the degree of knowledge elicited depending on the characteristics of the task.

Together, these results challenge the cognitive view of knowledge as a stable and coherent mental entity in the minds of individual learners. The knowledge demonstrated by learners is sensitive to various aspects of the tasks used to elicit them. There are at least two important practical implications of the situated view of science knowledge. First, the situated view further emphasizes the importance of creating learning opportunities that account for how tasks interact with learners' characteristics, such as individual differences in prior knowledge and cognitive ability. Second, and more importantly, mature understanding of scientific concepts may be conceptualized as reduction in the interaction between individual and situational variables. That is, as a learner's understanding of a concept develops, their performance on tasks requiring this knowledge is less influenced by representations, questions, and task features.

Misconceptions are the result of heuristic, rather than logical, reasoning

The second important area of progress in conceptual change theory is in our understanding of the underlying conceptual structures that produce misconceptions. An important implication of the *knowledge-as-elements* approach is that students' naïve knowledge is best understood in terms of implicit empirical assumptions and heuristic reasoning, as opposed to the empirical evidence and logical arguments favored in scientific practice. That is, although the goal of science education is to promote scientific thinking based on logical reasoning from evidence, novice science learners are much more likely to apply everyday thinking based on non-scientific assumptions and heuristics.

For example, Talanquer (2006) developed a framework for classifying common alternative conceptions in chemistry in terms of 5 empirical assumptions (*continuity, substantialism, essentialism, mechanical causality, teleology*) and 4 heuristic reasoning strategies (*association, reduction, fixation, linear sequencing*). Attempts to address misconceptions must therefore target common assumptions or heuristics that learners readily apply when encountering scientific concepts both outside and inside the classroom. This view also suggests that learning progressions involving conceptual change involves a change in both underlying knowledge (from empirical assumptions to evidence) and reasoning (heuristic to logical arguments) (Berland & McNeill, 2010; Maeyer & Talanquer, 2013; Mohan, Chen, & Anderson, 2009; Talanquer, 2009).

Naïve knowledge structures are suppressed, not supplanted

Finally, recent research employing reaction time and brain imaging methods support the view that naïve ideas about scientific phenomena continue to influence cognitive processes, even in experts with mature scientific understanding. In a study conducted by Shtulman and Varcarcel (2012), experts where asked to determine whether statements were true or false as quickly as possible. There were two types of statements: statements with truth-values consistent across naïve and scientific theories (e.g. “The Moon revolves around Earth”) and statements with truth-values inconsistent across naïve and scientific theories (e.g. “Earth revolves around the Sun”). The results showed that experts were slower and less accurate at verifying inconsistent statements compared to consistent statements, across several domains. The authors conclude that misconceptions are suppressed, rather than supplanted by scientific knowledge. Additional reaction time and brain imaging studies have confirmed that intuitive ideas about scientific phenomena persist in experts (Babai, Sekal, & Stavy, 2009; Potvin, Masson, Lafortune, & Cyr, 2014; Masson, Potvin, Riopel, & Foisy, 2014). A similar phenomenon, called the continued influence effect of misinformation, has been previously documented in the memory literature (Johnson & Seifert, 1994).

Thus, conceptual change is not a process of replacing naïve ideas with correct ideas. Rather, conceptual change occurs when people learn to successfully suppress naïve ideas. This suppression, in turn, provides the setting for acquiring, strengthening, and activating scientifically accurate structures in working memory. Thus, conceptual change instruction should be focused on helping learners suppress naïve knowledge structures.

Defining 'scientific intuition'

Although the term *misconception* remains a useful term for referring to students' inaccurate in science education at large, recent developments in conceptual change research and the historical implications that comes with the use of the term suggest the need for a more precise phrase. Over the past several decades, researchers have introduced several terms to describe students' inaccurate science ideas, including *alternative conceptions* (Gilbert & Watts, 1983), *mental models* (Vosniadou & Brewer, 1992), *preconceptions* (Clement, 1993), and *naïve ideas* (Nehm & Ha, 2011). Based on the recent developments in conceptual change described above, these terms do not adequately account for the situated and heuristic nature of misconceptions. Further, they imply structural equivalence with scientific knowledge. That is, these terms do not make it clear that the nature of students' prior knowledge is qualitatively different from explicit scientific knowledge. To better capture these differences, I propose the use of the term *scientific intuition* to refer to the broad class of mental structures that are responsible for producing the scientific misconceptions observed regularly across people.

While *intuition* can be used in various ways in relation to science knowledge (see Bunge, 1962 for examples), for the purpose of this dissertation, I define *intuition* as: the unconsciously activated implicit knowledge structures that that underlie the explicit expressions of knowledge, such as predictions and reasoning about phenomena. *Intuitions* are the assumptions or biases that one considers to be likely or true without further conscious reflection or explanation. This definition of intuition follows accounts of the qualitative differences between implicit and explicit knowledge and memory (Dienes & Perner, 1999; Karmiloff-Smith, 1986; Schacter, 1987). *Scientific intuitions* are qualitatively distinct from the beliefs directly observed behaviors or explicitly expressed language used by people; they are the unobserved facts or associations that are true or likely given the observed behaviors and verbal expression. It is also important to note that the use of *scientific* here is not intended to suggest that these intuitions are derived in a scientific manner or through formal scientific practices. Instead, this use refers to the fact that intuitions are relevant to scientific phenomena.

Scientific intuition has several important characteristics that distinguish it from explicit, conceptual knowledge demonstrated in mature science understanding. First, *intuition* is gained through experience rather than reflection. Explicit knowledge may be gained through experience as well, but it also requires reflection and representation of general patterns perceived in the environment. Thus, one way to identify whether an idea or belief is intuitive is to determine whether or not it is congruent with covariance in the environment. For example, the scientific intuition *"small objects float"* reflects covariations found in people's everyday experiences with objects—objects that are small are more likely to float. The second important characteristic of intuitions is that they are heuristic, rather than deterministic, in nature. Unlike explicit factual knowledge or principles, scientific intuitions are not applied equally everywhere. For example, children often express the intuition about forces and motion that forces tend to "run out" or fade away, such as when a ball is thrown or rolled on a surface. Although this intuition can provide accurate predictions about a variety of phenomena, it cannot be applied universally in the same way *scientific principles,* such as Newton's Laws of Motion and Einstein's Theory of Relativity can.

An important consideration for the use of the term *intuition* is the relationship between the scientific intuitions of novices and experts. For both novices and experts, scientific intuitions provide a basis for making predictions and explanations about scientific phenomena. For novices, the application of the intuitions they have gained through experience may be congruent or incongruent with predictions based on scientific principles. On the other hand, science experts may also develop new scientific intuitions based on their knowledge of scientific principles through extensive experience with them. Like novices, experts apply intuitions to provide explanations and make predictions about scientific phenomena. However, experts' intuitions are grounded in assumptions that have been mathematically proven or empirically supported. For example, a physicist may have intuitions about how to apply scientific principles to solve problems related to force and motion (i.e. Chi, Feltovich, & Glaser, 1981). In both experts and novices, intuitions represent complex knowledge of scientific phenomena, and they are expressed rapidly and without need for explicit justification.

From this discussion of the scientific intuitions of novices and experts, two important ideas emerge. First, unlike the term *misconception*, intuitions do not imply scientific inaccuracy. Rather, intuitions reflect ideas assumed to be likely or true by a person, and serve as the basis for explanations, reasoning, or predictions. Second, intuitions must be considered in reference to a person for whom the idea is intuitive. For example, an expert may find the scientific conception of *force* (i.e. Newton's 2nd Law of Motion) and its application to be intuitive—the expert refers and applies this idea to novel situations without need to further reference the logical and empirical evidence. On the other hand, a novice does not find this idea intuitive, and may instead apply their own intuitive ideas of force in these situations. Put more generally, an idea or belief *X* may be intuitive to person *Y,* but not to person *Z.*

The use of the term *scientific intuition* is also intended to reflect current understanding of the role of prior knowledge in science learning. Researchers have demonstrated that inaccurate prior knowledge can be a valuable resource for science learning. For example, Smith, diSessa, and Roschelle (1993) demonstrated that students' prior knowledge provides raw material for formulating scientific theory, supports qualitative reasoning, and helps novices map everyday situations to scientific representations. This opposes the view of *misconceptions* as cohesive, stable ideas and beliefs that must be "replaced" or "overcome" through science instruction. Instead, scientific intuitions can be viewed as a source of predictions, explanations, and representations that can be addressed in an increasingly explicit manner through instruction.

This definition of the term *scientific intuition* also addresses discussions about the "grain size" of knowledge associated with conceptual change research. Chi (2008, 2013) describes multiple types and levels at which misconceived knowledge conflicts with scientific knowledge: *false beliefs, flawed mental models, category mistakes,* and *missing schema.* The definition of scientific intuitions can be applied to multiple levels of misconceived knowledge described above.

In the case of *false beliefs*, incorrect information that occurs at the level of a single idea, scientific intuitions may or may not be involved. A false belief such as "sharks do not suffer from cancer" may arise simply from the communication of misinformation. Often, these singular ideas can be traced back to a source of misinformation or cultural myth[1]. Other false beliefs may be specific instantiations of general scientific intuitions. For example, a student that endorses the idea that

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[1] For example, the false belief that sharks do not suffer from cancer can be traced back to the 1992 book *Sharks Don't Get Cancer* by I. William Lane. Sharks can indeed suffer from cancer.

“the heart oxygenates blood” as true, may be operating on the more general intuition that “the heart has important functions involving blood.” This belief is an intuition in that that is assumed to be likely or true (i.e. no further proof or explanation is necessary) and it may be learned from repeated experience with prevalent associations between the heart and vital life functions involving blood. Thus, the false belief that “the heart oxygenates blood” is intuitive for novices in the sense that it is congruent with more general intuitions about the importance of the heart and blood. Successful revision of this false belief has been achieved by either explicit or implicit refutation (Chi & Roscoe, 2002). The relative ease with which this belief is revised may be explained by the fact that the more general intuition (i.e. “the heart has important functions related to blood”) stays intact in the face of the refutation.

Another form of inaccurate knowledge, a *flawed mental model,* involves multiple, interrelated beliefs. For example, one topic in which misconceptions are commonly cited is the reason for seasonal differences in temperature on Earth. Novices often make assumptions about the changes in the distance between Earth and the Sun when explaining this phenomenon. In this case, one or more aspects of the learner’s mental model are inaccurate, missing, or incomplete. There are several scientific intuitions that are correct with this “inaccurate” model, such as that the Sun transfers energy to Earth and that being closer to a heat source transfer more heat. On the other hand, they likely do not have strong intuitions about the tilt of Earth’s axis and the differential heating caused by the angle of incidence of light. Thus, inaccurate knowledge at the *flawed mental model* level needs to be addressed by somehow maintaining and suppressing some parts of existing knowledge, while also connecting to new knowledge.

Other types of misconceived knowledge are described by Chi as “incommensurate knowledge,” which involves a fundamental misalignment between categories on lateral branches or ontological trees. For example, students often think of *heat* as belonging to the substance category. Assigning heat to this category means that it adopts the properties associated with that category– substances can be moved, trapped, and lost. However, a scientific understanding of *heat* views it as an emergent property. That is, the macroscopic phenomenon of heat emerges from the microscopic movement of molecules. Some theorists claim that conceptual change involves shifts in ontological categories (such as *substance* → *process*) or epistemological beliefs (such as the belief that "movement of inanimate objects requires explanation").

Ontological categories and epistemological beliefs are intuitive in that they are learned indirectly through experience, are assumed to be likely or true without further explanation. These categories and beliefs are gained without intention or direct instruction about them. Part of the difficulty in changing this type of knowledge is making learners aware that they have them in the first place. They are such an ingrained part of our everyday thinking that it is difficult to consider scientific phenomena without them. In fact, one of the recommended strategies for helping students is to provide explicit training on ontological categories (Slotta & Chi, 2006). While this type of instruction may be effective for some students, it is not clear why learning about ontological categories is likely to change them immediately – ontological categories and epistemological beliefs are gained through extended experiences that cause them to develop. Thus, it is more likely that these intuitions must be changed through circumstances similar to how they were developed.

Misconceived knowledge may also be "incommensurate" when a schema needed for accurate scientific knowledge is completely missing. This *missing schema* type of misconceived knowledge helps explain why some concepts are particularly difficult for students to acquire. Missing schema related to science concepts are often difficult to develop because people have difficulty developing intuitions for them because of complexity, scale, or abstractness. For example, statistical concepts related to probability are often difficult for people to learn because they do not have intuitions about abstract concepts like distributions and sampling. Thus, a challenge for science instruction is determining methods and means for helping students develop intuitions about unfamiliar and abstract concepts.

To give another example about how this definition of scientific intuition can be applied to understand inaccurate scientific knowledge, consider the example of *extramission beliefs.* Researchers have studied a flawed mental model related to human perception–the view that human vision is dependent on emissions output from the eye (for review, see Winer, Cottrell, Gregg, Fournier, & Bica, 2002). This misconception has been shown to be prevalent (in some cases, over 50% of adults demonstrate this belief) and persistent after instruction (Gregg, Winer, Cottrell, Hedman, & Fournier, 2001). To understand the source of this misconception, consider scientific intuitions related to “vision”: seeing involves light; light is usually emitted from a source (the Sun, bulb, fire, etc.); we see things we “point” or direct our eyes at; other devices that “see”—like radars and lasers—emit something in order to sense. These intuitive associations and heuristics are congruent with our everyday experiences and may lead to extramission beliefs under certain constraints, such as the words, images, and questions used to elicit these ideas (Winer, Cottrell, Karefilaki, & Gregg, 1996). Thus, while the results of this thinking are mistaken beliefs in light of scientific understanding, the sources of these mistakes are reconcilable in consideration of the everyday experiences of learners and the types of intuitive knowledge they glean from them.

In relation to the debate over the coherence of naïve scientific knowledge, the use of the term *scientific intuition* may provide a middle path that can explain both the coherence and incoherence of misconceptions. Scientific intuitions are robust in that they are learned from everyday experiences. Therefore, they are readily available and applicable to a wide range of phenomena. For example, our scientific intuition that gravity works in a downward direction is based on overwhelming information from the environment. A scientific notion of gravity as a force between any two bodies is much more difficult to grasp because we have few readily perceivable examples of this concept on which to develop intuitions. Thus, by sheer amount of experience, we are more likely to apply our scientific intuitions about gravity, rather than a scientific principle, in a given circumstance.

Misconceptions are also incoherent because they are based on *intuitions* that are applied in a heuristic, rather than deterministic, manner. In a given circumstance, a person may or may not apply their intuitions based on myriad factors, such as the questions, prompts, images, or words used to elicit knowledge. Application of intuitive knowledge might also depend on whether intuitions are intentionally and explicitly mentioned, and if so, whether they are put in a positive or negative light.

This brief discussion will not likely put to rest debates about the coherence of misconceived scientific knowledge. However, the definition of *scientific intuition* I have offered attempts to reconcile common qualities of the mental entities that have been theorized to account for conceptual change. Whether we are talking about *p-prims, facets*, *ontological categories, epistemological presuppositions,* or *flawed mental models,* these cognitive elements are (a) gained early and through experience, (b) reside largely outside of conscious reflection, and (c) are robust to change from singular experiences that conflict with them.

In this chapter, I reviewed past and recent conceptual change literature, describing the implicit knowledge structures (core knowledge, ontological categories, epistemological beliefs, *p-prims*) various models suggest are involved in conceptual change. These knowledge structures can be classified under a more general category of knowledge, defined as *scientific intuitions. Scientific intuitions* are general assumptions and heuristics, gained through experience, that are unconsciously applied to predict and explain scientific phenomena. To better understand how *scientific intuition* develops and changes, Chapter 2 describes research on *implicit learning.*

Chapter 2: Implicit Learning as a Source of Scientific Intuitions

This dissertation research is based on the claim that *implicit learning*–the acquisition of complex knowledge in the absence of intention or awareness—plays an important role in the development of scientific knowledge. In the previous chapter, I described the implicit knowledge structures previous models of conceptual change rely on to explain students' difficulties in learning science. In this chapter, I discuss how theory and research on implicit learning may provide insight into cognitive processes associated with these implicit knowledge structures. Specifically, I argue that implicit learning processes are a source of scientific intuitions, as previously defined. I begin by providing an overview of implicit learning research. Then, I discuss connections between implicit learning and scientific knowledge by providing evidence from developmental psychology, cognitive psychology, and conceptual change research. I conclude by arguing that implicit learning processes play a critical role in the development of scientific intuitions important for conceptual change.

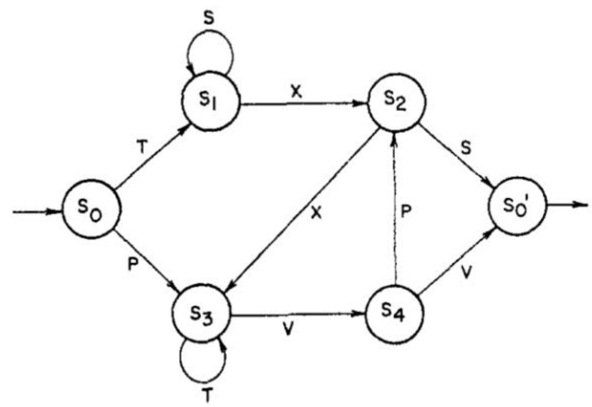
A Brief Review of Implicit Learning

Implicit learning (Berry & Dienes, 1993; Cleeremans, Destrebecqz, & Boyer, 1998; Frensch & Rünger, 2003; Reber, 1989; Seger, 1994; Shanks 2004) refers to the acquisition of knowledge in the absence of intention and lack of awareness of the knowledge learned. Over the past 5 decades, research has demonstrated that people, over a range of tasks, have the ability to learn complex patterns in an incidental manner. Several aspects of implicit learning have been studied, qualities of implicit learning that differentiate it from explicit learning, cognitive models of implicit learning, and psychometric qualities and neural bases of implicit learning abilities.

Qualities of implicit learning tasks

Reber (1967) coined the term ‘implicit learning’ to describe participants’ performance on an artificial grammar task. In an artificial grammar (AG) task, strings of letters generated from a set of rules (often represented by a Markov chain) are presented with the instruction to simply remember as many letter strings as possible. Later, participants are tested on their ability to discriminate between novel grammatical and non-grammatical letter strings. Results from studies show that participants are able to accurately classify letter strings above chance; however, participants are not able to accurately describe the underlying rules of the grammar. Thus, the learning that occurs in these tasks is implicit in the sense that performance on novel tasks improves in the absence of conscious knowledge of what informs performance.

Similar results have been found across a range of tasks. In sequence learning, or *serial reaction time (SRT) tasks* (Nissen & Bullemer, 1987), a target, such as a dot, is presented in one of several locations; the subject’s task is to respond to the dot location by pressing the corresponding key as quickly as possible. Unbeknownst to the subject, the sequence of locations follows a complex pattern (e.g. repeating 10-unit long sequence). Reaction times for locating the target decrease over several training sessions of the sequence; when a random sequence of target locations is introduced, the reaction times significantly increase, demonstrating that learning of the structured sequence occurred. However, when probed about the sequences of locations, participants cannot reliably report the patterns used to improve performance. Variations in the SRT tasks include manipulations to the structure of sequences (Cohen, Ivry, & Keele, 1990), alternating between sequenced and random locations (e.g. ASRT, Howard & Howard, 2001), addition of a secondary task to divert attention and memory (e.g. Shanks & Johnstone, 1999), and variation in probes for explicit knowledge of the learned patterns (Destrebecqz & Cleeremans, 2001).



TSXS	TSSSXXVV	TSSXXVPS	PTTVV	PVPXVPS
TXS	TXXVPXVV	TSXXTVPS	PVV	PTVPS
TSSSXS	TXXTTVV	TXXTVPS	PTVPXVV	PVPXTVPS
	TSSXXVV	TXXVPS	PVPXVV	PTTTVPS
	TSXXTVV		PTVPXTVV	

Figure 2.1. A Markov Chain representation of rules governing a finite-state artificial grammar. Examples of grammatical letter strings generated by artificial grammar rules. (Figures originally from Reber, Kassin, Lewis, & Cantor, 1980)

In *process control tasks* (Berry & Broadbent, 1984), participants attempt to control the output a system by manipulating the inputs to that system. For example, in the *sugar factory task*, participants take on the role of a plant manager that changes the number of workers in order to achieve a certain output of sugar. Unbeknownst to the participants, the underlying algorithm that follows a function dependent on the previous output. Participants are able to maintain the target level of output, despite inability to describe the rules used to achieve that output.

Probabilistic classifications tasks, such as the “weather prediction task,” require participants to make predictions between two classes (e.g. “rainy” or “sunny”) based on multiple stimuli (Knowlton, Squire, & Gluck, 1994). For example, each combination of one, two, or three stimuli cards containing different geometric shapes produce one condition or another in a probabilistic manner. If two of the cues were present, they might result in “rainy” weather 18% of the time. Knowlton and colleagues (1994) found that amnesiac patients were able to associate cues with outcomes at the same rate as control subjects. Further, learning could not be explained by cue-response information being held in short-term memory, suggesting that performance improves based on long-term, non-declarative memory. Thus, implicit learning is preserved in patients with damage to brain areas associated with explicit, declarative learning.

The various tasks used to study implicit learning share several features in common. First, stimuli are governed by an underlying complex set of rules or sequences. The rules or sequences are complex in that rules involve multiple operations (e.g. Markov chain) and sequences involve associations of 3 or more stimuli. Thus, it is difficult for participants to deduce the governing rules or sequences through explicitly searching or testing. Second, evidence for implicit learning comes from participants' performance, measured by changes in accuracy and reaction times to stimuli. Increases in accuracy above chance and lower reaction times across trials indicate implicit learning. Third, task protocols probe explicit knowledge through direct assessment, think-aloud procedures, or other declarative explanations. Lack of ability to describe the patterns governing the cue-response patterns provides additional evidence for implicit learning.

Research has focused on determining whether implicit learning can be distinguished from explicit forms of learning (for reviews, see Frensch & Rünger, 2003; Seger, 1994; Shanks, 2004). Implicit learning can be qualitatively differentiated from explicit learning in several ways. Explicit learning processes have been characterized as similar to conscious problem solving, which involves building and testing hypotheses and mental models (Mathews et al., 1989). Explicit learning processes are slow, controlled, require higher effort, and can process a relatively limited amount of information. On the other hand, the processing involved in implicit learning is characterized as automatic, rapid, associative, probabilistic, requiring low effort, and with a high capacity for information processing (Evans, 2008).

In addition to these broad qualitative differences, three aspects of implicit learning have been used to operationalize differences with explicit learning: *lack of intention, lack of awareness,* and *lack of attention*. First, implicit learning can be characterized by *lack of intention* to learn the targeted information. This is often operationalized by varying the instructions and goals given during experimental tasks. Typical implicit learning protocols guide participants to memorize a set of letter strings (artificial grammar task – Reber, Kassin, Lewis, & Cantor, 1980), respond as quickly as possible to an object location (serial reaction time task – Nissen & Bullemer, 1987), or attempt to maintain a particular output (process control task – Berry & Broadbent, 1984). Learning instructions for the same tasks can be made more explicit in at least two ways: by instructing participants to seek the underlying rule or pattern that governs the display or system (e.g. rule-finding or hypothesis-testing) or by presenting explicit information about or representations of the rules or patterns that govern the system prior to observation of exemplars. For example, in study conducted with older (age = 60-80) and younger (age = 20-23) populations, researchers manipulated whether or not task goals directed people to look for a rule governing an artificial grammar (Howard & Howard, 2001). The results of the study showed that explicit task instructions can negatively influence performance in older, but not younger, populations, suggesting that *lack of intention* can be beneficial for learning under some conditions.

Second, participants typically *lack awareness* of what they have learned during an implicit learning task. Researchers operationalize *lack of awareness* by comparing changes in performance and explicit, declarative knowledge. In implicit learning tasks, performance typically improves (i.e. higher accuracy and/or lower reaction time) despite a lack of a parallel increase in explicit, verbalizable knowledge during implicit learning tasks (Seger, 1994). Conscious access or awareness of knowledge (or lack thereof) is assessed through verbal reports, forced-choice recognition, or subjective recognition ratings performed during implicit learning tasks (Cleeremans, Destrebecqz, & Boyer, 1998). Although researchers do not agree on whether entirely nonconscious knowledge exists (e.g. Frensch & Rünger, 2003; Perruchet & Vinter, 1997; Shanks & St. John, 1994), there remains a sense that a gap exists between what is learned and awareness of what is learned during implicit learning tasks. This "performance/verbalizable knowledge" gap (Berry & Broadbent, 1984) has generated extensive writing and empirical studies of implicit and explicit modes of learning, even though this distinction has largely drawn attention away from the mechanisms responsible for implicit learning (Frensch & Rünger, 2003).

Third, implicit learning has been characterized in terms of *lack of attention.* To examine the role of attention in implicit learning, researchers have employed secondary distracter tasks that divert attention away from implicit learning stimuli. For example, Nissen & Bullemer (1987) used a secondary tone-counting task to show that sequence learning is reduced when attention is diverted, suggesting some form of attention is necessary for learning to occur. However, other studies have shown that learning occurs despite diverted attention (Cohen, Ivry, & Keele, 1990; Jiang & Chun, 2001; Seger, 1994; Turk-Browne, Jungé, & Scholl, 2005). For example, in a visual search task, participants look for a target (a horizontal 'T' pointing left or right) among distractors (rotated black 'L's), responding by indicating the direction the bottom of the 'T' is pointing. People are able to learn associations between the background stimuli (*global context)* associated with target locations to facilitate search; this is known as *contextual cueing* (Chun & Jiang, 1998). When multiple contexts are presented (i.e. black and white distractors), both attended and ignored contexts can facilitate visual search. However, the expression of this learning depends on how attention is focused during transfer tasks (Jiang & Leung, 2005). Thus, while the expression of implicit learning demonstrated in *contextual cueing* requires some form of attention, latent learning may occur in the absence of attention.

To summarize, implicit learning describes learning that occurs despite (1) *lack of intention* to learn (as operationalized by task instructions), (2) *lack of awareness* of what has been learned (shown by inability to consciously access knowledge), and (3) *reduced attention* to stimuli during learning (operationalized by employing secondary tasks). In addition to these general qualities of implicit learning, research has also focused on establishing the independence of implicit learning by providing evidence from psychometric and neuroimaging data.

Implicit learning as a distinct cognitive ability

Implicit learning ability can be distinguished from explicit abilities based on how its psychometric properties relate to individual differences in other cognitive abilities and traits. For example, psychometric intelligence (*g*) dissociates implicit and explicit learning performance, with implicit learning uncorrelated with intelligence (Gebauer & Mackintosh, 2007). Similarly, Kaufman and colleagues (2010) found that implicit learning ability is weakly correlated with general intelligence and unrelated to working memory ability. On the other hand, implicit learning ability measured by the SRT task is correlated with personality traits such as openness and impulsivity. Further, compared to explicit reasoning and problem-solving abilities, there is less variation in implicit learning ability in the population and across ages (Howard & Howard, 2001; Frensch & Rünger, 2003). While these distinct psychometric qualities of implicit learning provide evidence of separate learning mechanisms for implicit and explicit learning, it is possible that there are multiple implicit learning abilities exist, as measures of different implicit learning tasks are not strongly correlated with one another (Gebauer & Mackintosh, 2007).

Research in cognitive neuroscience also suggests dissociation between implicit and explicit learning processes. Reber (1993) proposed that implicit learning systems developed earlier evolutionarily than explicit systems, predicting that implicit learning abilities would be preserved in patients with amnesia caused by damage to the medial temporal lobe. Studies of amnesiac patients have shown that they do in fact retain implicit learning abilities, despite inability to form new declarative memories associated with explicit learning (Knowlton, Rasmus, & Squire, 1992; Nissen & Bullemer, 1987). Further, recent brain imaging studies suggest that brain networks important for implicit learning are distinct from networks associated with explicit learning (Karabanov et al., 2010; Poldrack et al., 2001; Seger, Prabhakaran, Poldrack, & Gabrieli, 2000; Yang & Li, 2012). Taken together, these findings suggest that implicit and explicit learning rely on different cognitive mechanisms.

To summarize, implicit learning can be thought of as an unintentional, domain-general mechanism capable of gleaning complex information about patterns and sequences in perceptual stimuli that is not readily available to conscious report. This ability is differentiated from explicit forms of thinking in that it is dissociable from psychometric intelligence (*g*) and working memory ability, and may be supported by distinct brain networks. Although mounting evidence from psychometric and neuroimaging research supports implicit and explicit learning as separate abilities, ongoing debates about the relationship between implicit learning, explicit learning, and awareness (see Frensch & Rünger, 2003) highlight the lack of understanding about the cognitive mechanisms that support implicit learning. One key issue for implicit learning research is determining whether multiple, separate cognitive mechanisms are responsible for implicit and non-implicit learning, or if a single, shared mechanism generates knowledge both in and out of awareness. In the following section, I describe two possible cognitive mechanisms to account for implicit learning phenomena.

Cognitive models of implicit learning

To explain the ability of people to learn structural contingencies without intention, awareness, and attention across complex visual and auditory stimuli, researchers have developed models of the cognitive processes underlying implicit learning phenomena (Perruchet & Pacteau, 1990; Shanks & St. John, 1994). Perruchet and Pacteau (1990) argue that implicit learning can be accounted for by the formation of knowledge fragments or “chunks” of associations between sequential or co-occurring stimuli. For example, people develop conscious knowledge of parts of a complex sequence (e.g. ‘T is followed by S’), rather than an unconscious representation of the underlying structure. In an artificial grammar task, people were able to recognize grammatical pairs of letters that are grammatical (Perruchet & Pacteau, 1990), and this knowledge is sufficient to account for performance on a standard test of grammaticality. This “chunking” view of implicit learning suggests that implicit learning isn’t unconsciously held. Rather, minds are able to develop “chunks” of information about statistical regularities in stimuli in memory. As these chunks become more discrete over time, people are better able to report them consciously. Further support for this model comes from studies that show that learning in an implicit learning task (SRT) is associated with working memory capacity when the response-to-stimuli interval (RSI) is lengthened to 300 ms (Martini, Furtner, & Sachse, 2013). Thus, implicit learning in some circumstances may involve holding information in conscious memory.

Others have modeled cognitive processes involved in implicit learning using computational models, such as connectionist or parallel distributed process (PDP) computational models (Davies, 1995; Rumelhart, Hinton, & McClelland, 1986). These models propose that information is processed by networks of *processing units* that are activated and inhibited according to simple calculation rules for *propagation*, *activation*, and *learning*. Unit activations and connections are able to capture information and “learn” about the underlying structure of the environment. Rather than occurring in discrete units or representations, information is widely distributed across the processing system, allowing for quick activation from partial or ambiguous representations (Kihlstrom, 1987). These computational models provide explanation for the qualitative features of implicit learning—fast, simultaneous, robust, and automatically activated. While there is currently no conclusive evidence for one computational model over another, it is important to note that these models can distinguish implicit learning processes from more explicit, conscious processes.

Taken together, these findings from psychology, psychometrics, neuroscience, and cognitive psychology provide evidence for qualitative and quantitative differences between implicit and explicit learning. Implicit learning can be thought of as a domain-general cognitive process that gleans complex patterns and sequences from perceptual stimuli; this information is activated automatically, yet is not readily accessible by conscious report. Implicit learning ability is differentiated from explicit forms of thinking and is dissociable from psychometric intelligence (*g*) and working memory ability, and may be supported by distinct brain networks. Cognitive models account for implicit learning phenomena based on models of attention, working memory, and computational models. Having established evidence for distinct implicit learning processes in human cognition, I continue by exploring evidence that implicit learning is involved in the development of scientific knowledge.

Implicit Learning as a Source of Scientific Intuitions

What evidence do we have that implicit learning processes are involved in the development of scientific knowledge? While it should be made clear that I do not suggest that *all* knowledge of scientific phenomena is implicitly learned, there is an evidence that it does play a significant role. My interest lies in describing how pre-instructional cognitive artifacts proposed by conceptual change theorists, such as epistemological commitments, ontological categories, and *p-prims,* can be acquired and changed via implicit learning processes. In this section, I present evidence to support the claim that the scientific intuitions important for conceptual change originate from implicit processes.

First, the presence of implicit science knowledge early in life suggests that intuitions may be acquired through implicit learning. As early as infancy, humans demonstrate knowledge about the causal rules that govern the physical world and show novelty responses for events that appear to violate those rules (Baillargeon, 1995, 2002; Keil, 2011; Spelke, 1990, 1991). For example, Newman and colleagues (2008) presented 7-month-old infants with collisions between two balls (i.e. Michotte collisions), observing looking behaviors for physically possible and impossible events. Results of several experiments showed that infants look longer at impossible causal events (delay between collision and motion) than at possible causal (no delay between collision and motion) after being habituated to various types of causal events. The authors concluded from several experiments manipulating the temporal delays and complexity of displays that infants are able to perceive causality in these events (Newman et al., 2008).

The ability to perceive causality develops early, this knowledge does not likely develop through explicit, conscious cognitive processes. While some developmental psychologists suggest that children engage in sophisticated theory testing (e.g. Gopnik, 1996), the cognitive mechanisms and brain areas associated with conscious problem solving do not develop until late childhood, extending into adolescence (Zelazo, 2004; Zelazo, Carlson, & Kesek, 2008; Zelazo, Craik, & Booth, 2004). For example, when presented with a simple task-switching paradigm (i.e., the Dimensional Change Card Sort), 3-year-olds tend to perseverate on a previous rule (e.g. 'match objects based on shape') after they have been told to switch to a new rule (e.g. 'match objects based on color'). That is, young children lack the ability to encode multiple rules to the same stimulus (Zelazo, 2004). Thus, the ability to see the same thing from multiple perspectives, a critical skill for scientific reasoning and hypothesis testing, is not available early in life. On the other hand, researcher have theorized that implicit learning mechanisms develop early (in both ontogeny and phylogeny) and require low-level selective attention, as opposed to effortful, systematic experimentation (Reber, 1989). Thus, the presence of sophisticated science knowledge early in life may not reflect conscious problem solving, but rather implicit learning of environmental regularities that correspond to scientific concepts.

Children's implicit knowledge of causal physical laws may reflect their lack of ability to differentiate between improbable and impossible events. For example, Shtulman & Carey (2007) presented stories about events that were possible (e.g. eating an apple, building a house out of bricks), impossible (e.g. turning applesauce back into apples, walking through a brick wall), and improbable (e.g. drinking onion juice, making a mug-shaped building). Stories were designed to include events that violated physical laws. Children and adults were asked to classify events as possible, impossible, or improbable, as well as providing reasoning for their answers. The results showed a developmental trend, where adults were more likely to differentiate between impossible and improbable events, while younger children were less likely to make this differentiation. That is, 4-year-olds do not readily differentiate between events that are physically impossible and events that are simply unlikely to happen.

Further, when children report about the causes of events, they are less likely than adults to refer to physical laws or facts in their justifications (Shtulman & Carey, 2007). Rather, they often provide redundant ("that is impossible") or hypothetical ("something else would happen instead") justifications for their judgments. Even though children can differentiate between possible and impossible events, this may reflect their knowledge of the probability of events in the world rather than knowledge of the mechanisms by which they can or cannot occur. This also suggests that the information that people learn about the world is probabilistic, rather than deterministic, in nature. One explanation for this observation is that early learning is implicit in nature, leading to knowledge that is statistical in nature (Perruchet & Pacton, 2006).

While it should be noted that there is considerable debate about whether knowledge about perceptual causality is innate or learned (see Cohen & Oakes, 1993; Leslie & Keeble, 1987; Oakes & Cohen, 1990), the relevant conclusions from this research are (a) implicit knowledge of causality in physical events appears early in life, and (b) this knowledge is not dependent on explicit, conscious reasoning abilities. This evidence supports the claim that implicit scientific knowledge can develop in the absence of mature, conscious thinking abilities associated with scientific reasoning, such as logical reasoning, symbolic representation, and abstract thought.

A second piece of evidence for implicit learning in science comes from conceptual change literature in the characterizations of the prior knowledge structures involved in models of science learning. These descriptions share many qualities of implicitly-learned knowledge – they occur in the absence of awareness and intention to learn. For example, in describing the development of *p-prims*, diSessa (1993) states that they "often originate as minimal abstractions of common phenomena" (p. 114). Later, he states, "I presume that conscious access to their application is very limited … Subjects may make predictions on the basis of a *p-prim*, but the prediction is not the *p-prim*" (p. 119). Thus *p-prims*, as described, exist in the absence of awareness of what has been learned or applied. Sodian, Zaichik, & Carey (1991) provide a further statement of lack of awareness of early scientific knowledge: "…while young children may construct intuitive theories of the world, they lack metaconceptual awareness of this fact" (p. 753). This difference between naïve knowledge and scientific is emphasized again by Vosniadou: "children are usually not metaconceptually aware of their beliefs…" (p. 122). Similarly, Chi (2005) in describing how ontological classes are learned says that they can be easily learned because "the shared features are often perceptually salient and can be intuitively grasped as similar … without the need of being told" (p. 177). That is, scientific knowledge about ontological classes can be acquired in the lack of *intention* and effort. In a recent example, researchers studying intuitive biological knowledge described what they call "cognitive construal" as being tied misconceptions about evolution (Coley & Tanner, 2015). According to these researchers, "[a] cognitive construal is an intuitive, often implicit, way of thinking about the world" (Coley, Arenson, Xu, & Tanner, 2017, p. 2).

Taken together, researchers have proposed and described different types of mental structures of prior scientific knowledge, and this knowledge shares many qualities with the knowledge that is gained through implicit learning. This knowledge is held largely in the absence of awareness and is automatically activated. What is missing from these descriptions is *how* these mental structures are acquired. While I acknowledge the possibility of innate mental structures, one goal of this dissertation is to demonstrate that these types of structures can be learned through implicit learning techniques. I continue to develop this case in the next chapter, which offers strategies for applying implicit learning to science learning.

Chapter 3: Using Implicit Learning to Enhance Conceptual Change Instruction

Several decades of research in science instruction have led to the conclusion that conceptual change is a slow, effortful process (Carey, 2000; Chi, Slotta, & deLeeuw, 1994; diSessa, 1982; Guzzetti, Snyder, Glass, & Gamas, 1993; Özdemir & Clark, 2007; Smith & Carey, 1985; Vosniadou, 1994). The instructional approaches used to encourage conceptual change processes have been largely explicit and intentional in nature (e.g. Sinatra & Pintrich, 2003). Before describing how implicit learning can be utilized to address conceptual change in science, I discuss some of the challenges of explicit forms of instruction in inducing conceptual change, particularly in relation to the notion of *cognitive conflict*. Then, I offer examples and principles for applying implicit learning to conceptual change in science.

Challenges of Explicit Instruction for Conceptual Change

Explicit instruction involves the direct presentation of concepts, explanations, and arguments to the learner as declarative knowledge, theories, or model representations. Explicit instruction, like direct instruction, can be an effective method to teach complex ideas, avoiding incorrect feedback and encoding errors that may lead to ambiguous knowledge structures (Klahr & Nigam, 2004). For example, learning science researchers have found that direct instruction delivered via cognitive tutors can be an efficient way to teach algebra, geometry, and some scientific reasoning strategies (Koedinger & Anderson, 1997; Sao Pedro, Gobert, Heffernan, & Beck, 2009). Science concepts can be presented explicitly through a variety of media, including text, teacher talk, demonstrations, and video. Although seemingly straightforward, there are several reasons why explicit instructional methods may be ineffective.

First, scientific representations used to instruct students explicitly may be scientifically inaccurate or obtuse. Irrelevant details can lead to reduced learning, especially when extraneous information is interesting to the learner (Mayer, Griffith, Jurkowitz, & Rothman, 2008). Further, these representations can actually be a source of misconceptions if they are unclear or lack coherence (Goldman & Bisanz, 2002). Even when learners are given representations that are scientifically accurate and concise, these depictions may not be fully comprehended in light of naïve knowledge structures because the learner lacks requisite knowledge for understanding new or conflicting information.

Attempts to explicitly correct inaccurate information may also backfire. Studies on political and health misperceptions have attempted to explicitly correct people's incorrect beliefs by presenting them as "myths." Remarkably, these attempts can result in increased acceptance of wrong information (Ecker, Lewandowsky, & Tang, 2010; Nyhan & Reifler, 2015). Because explicit corrective messages must be recalled to memory, people with lower ability to recall facts (such as novices, young and elderly people) are more susceptible to these so-called backfire effects (Ecker, Swire, & Lewandowsky, 2014).

One widely-studied strategy of explicit instruction for conceptual change is the use of refutation texts (for reviews, see Guzzetti, Snyder, Glass, & Gamas, 1993; Tippett, 2010). In this method, a learner reads text in which a common misconception is explicitly presented (e.g. "Many people believe…"). This is followed by a refutation cue statement (e.g. "However, this is not scientifically correct"), which is then followed by a scientific explanation. Researchers have examined how activation of prior knowledge, text format and structure, and reading processes and strategies influence conceptual change. While research has shown that refutation texts are generally effective, their effectiveness may be influenced by the grain size of the knowledge representations being addressed. For example, Chi (2008) suggests that while refutation texts may be effective for changing single faulty ideas, they may not be sufficient for addressing more robust, flawed mental models and categories.

Explicit instructional strategies, such as refutation text, depend on the successful activation and coordination of multiple cognitive resources and processes. First, learners must encode a refutation cue (e.g. “Some people hold the incorrect belief that…”). This cue is intended to activate prior knowledge, and signals to the learner that the information to follow is scientifically incorrect (Alvermann & Hague, 1989; Guzzetti, 2000). Accurate information must then be presented in a manner that is understandable, credible, and useful (Mason & Gava, 2007). According to the co-activation hypothesis (Kendeou & van den Broek, 2007), it is critical that scientifically accurate information is co-activated with previous inaccurate knowledge in working memory. This co-activation can lead to cognitive conflict, which produces additional processing and increases the likelihood of knowledge revision (Kendeou & O’Brien, 2014). Because each aspect of explicit conceptual change instruction relies on attention and working memory resources, these techniques are likely to fail when cognitive resources are limited due to lack of ability, experience, time, or a combination of these factors.

Further, explicit instruction techniques rely on the assumption that learners are rational thinkers. That is, given the appropriate information, learners are expected to make rational decisions about what is correct and what is incorrect. Research on the psychology of decision-making has shown that under various conditions, people are not rational and make decisions that are systematically biased (Kahneman & Tversky, 1979; 1982; Tversky & Kahneman, 1974; 1983). For example, studies on the framing effect demonstrate that people react differently to choices that are logically equivalent when those choices are framed positively or negatively (Tversky & Kahneman, 1981; Druckman, 2001).

Explicit conceptual change instruction has been shown to be effective when naïve scientific ideas occur at a relatively small conceptual grain size (Guzzetti, Snyder, Glass, & Gamas, 1993; Tippett, 2010). For example, refutation texts can effectively correct single incorrect ideas such as “the heart oxygenates blood” or “camels store water in their humps” or “the North Star (Polaris) is the brightest in the night sky.” However, naïve ideas in science often occur at a larger grain size, caused by a flawed mental model or mistakes in the categorization of concepts (Chi, 2008). While a mistaken belief or set of beliefs can be explicitly demonstrated, making learners aware of categorical errors is difficult to achieve explicitly. For example, it is not easy to put into words why electricity flowing through a wire is not like water flowing through a pipe. While there are many perceptual similarities, applying the properties of one to the other would lead to incorrect predictions and mistaken beliefs. Critically, learners must become aware of these category mistakes before they can build new conceptual structures to accommodate scientific phenomena (Chi, 2008). Thus, explicit instructional methods may be inadequate for making learners aware of the conflict between their prior knowledge and scientific concepts when they conflict at a categorical level. Although conceptual change via explicit and intentional instruction can be effective in some cases, other strategies are needed for learning contexts where students have limited cognitive tools and resources, or when learning involves more complex knowledge structures.

The role of cognitive conflict in conceptual change

Conceptual change researchers have long theorized that *cognitive conflict* plays a critical role early in conceptual change processes (Hewson & Hewson, 1990; Posner et al., 1982; Strike & Posner, 1992; Ramsburg & Ohlsson, 2016; for review, see Limón, 2001). Posner and colleagues (1982) proposed that the first stage of conceptual change involves dissatisfaction with current conceptions. Cognitive conflict is the basis for instructional techniques such as refutation texts (Guzzetti, Snyder, Glass, & Gamas, 1993) and discrepant events (Fensham & Kass, 1988). Discrepant events (along with related strategies such as presenting counterintuitive evidence and invoking prediction errors) are learning situations designed to demonstrate inconsistencies between the ways students perceive or think about the world and the scientific concept that they are intended to learn. The results of studies on the effectiveness of cognitive conflict strategies are mixed; while some research supports the effectiveness of these techniques, other research shows that they can be ineffective, and worse detrimental, to student learning. Further, there is a lack of understanding of the underlying cognitive mechanisms involved in cognitive conflict and how they support conceptual change in science education.

Some research studies have supported the cognitive conflict strategy as effective for inducing conceptual change. For example, Kang, Scharmann, & Noh (2004) showed middle school students a series of discrepant events—demonstrations that provide novel experiences and outcomes that contradict prior intuitions about scientific phenomena. Then, students engaged in a computer-based instructional activity, which served as a conceptual change intervention. By assessing the degree of conceptual conflict during these demonstrations and the change in students' conceptual knowledge afterward, researchers concluded that increased conceptual conflict was associated with increased conceptual knowledge.

However, other studies have shown mixed results associated with cognitive conflict. For example, Dreyfus, Jungwirth, & Eliovitch (1990) introduced conceptual conflict during interviews with 16-year-old students about common intuitions about scientific topics. Although they found evidence suggesting cognitive conflict occurred, students failed to achieve meaningful conflict. That is, students experienced conflict between their prior knowledge and scientific explanations, but were unable to make sense of the reasons for the conflict. The inability of learners to achieve meaningful conflict has been found in other studies (Chan, Burtis, Bereiter, 1997), and is in line with findings that students facing anomalous data demonstrate many different responses that do not lead to conceptual change, such as ignoring, rejection, uncertainty, exclusion, abeyance, and reinterpretation (Chinn & Brewer, 1998). Lack of meaningful conflict reduces the likelihood that this conflict will be appropriately resolved and result in conceptual change will occur (Limón, 2001).

A further problem of with conceptual conflict approaches is that they may only result in superficial changing of concepts. In a study of 9th grade Korean students, Lee and Byun (2012) found that the most common response to cognitive conflict was what they called "superficial theory change" in which students accepted the anomalous data as valid, abandoned their prior knowledge, but were unable to provide an explanation for the data. Students that have undergone "superficial theory change" may appear to have changed their conceptions in written and verbal reports, but lack understanding of the underlying scientific concept. The researchers also measured aspects of cognitive conflict–recognition, interest, anxiety, and reappraisal. They found that anxiety was critical component of cognitive conflict, and that higher levels of anxiety reduced the effect of cognitive conflict on student learning. Thus, conceptual conflict may also have the unintended effect of causing anxiety among students, which in turn can have a negative impact on learning.

Researchers have also demonstrated that conceptual change can occur in the absence of conceptual conflict. Ramsburg & Ohlsson (2016) developed a categorization task to examine non-monotonic learning of a category. Participants were trained to categorize images of fictional bacteria (i.e. whether it is oxygen-resistant or not) using information about 6 different characteristics (e.g., nuclei, cell wall, ribosome shape), each with two possible levels. They initially learned to categorize based on a misconception feature (i.e. *black nuclei*). After initial learning, the feature determining category membership changed to a new target feature (i.e. "bent ribosomes"). This target learning occurred either with or without disconfirming evidence. That is, half of participants received feedback that contradicted their previous categorization (complete condition) and half received only feedback confirming the new feature association (confirmation-only condition). The results showed that participants in the confirmation-only condition not only learned the new category, they learned it faster than those that received disconfirming evidence. The authors of the study concluded that at least one form of conceptual change, category change, is possible in the absence of cognitive conflict.

Taken together, research on cognitive conflict brings into question its relevance in conceptual change processes. While it has been proposed as a valuable method for addressing prior, inaccurate knowledge about scientific phenomena, the value of cognitive conflict as a general strategy has not been well-established. One particular challenge of this strategy is that explicit refutation or falsification of prior knowledge may have negative effects on learning—refuting a previous belief can unintentionally reinforce inaccurate beliefs and information that falsifies prior concepts can impede learning of the new concepts. Further, conceptual conflict strategies may not be helpful for all students. Researchers have suggested that while cognitive conflict may be beneficial for students with high academic achievement backgrounds, it may hinder learning for low-achieving students (Limón, 2001; Zohar & Aharon-Kravetsky, 2005).

If there is a role for cognitive conflict in conceptual change, it is possible that the amount of cognitive conflict is important. As described above, high levels of conflict may hinder conceptual change. This raises the possibility that smaller degrees of conflict that do not involve overtly rejecting inaccurate beliefs (such as in refutation texts) or presenting falsifying information (such as in discrepant events), may be more effective in inducing conceptual change. Research on implicit learning offers important insights into how these processes can be leveraged for conceptual change in science learning. In particular, I continue by discussing how implicit learning can help understand the role of *cognitive conflict* in conceptual change.

Implications of Implicit Learning Research for Conceptual Change

Research on implicit learning provides key insights into how and why this form of learning can enhance conceptual change processes through indirect conceptual conflict. Evidence comes from two types of implicit learning studies: (1) experiments examining how implicit learning interacts with prior knowledge, and (2) experiments that examine how implicit learning tasks can lead to the development of explicit, conscious knowledge offer key insights.

Researchers have found that violating expectations based on prior general knowledge can enhance implicit learning. Ziori, Pathos, and Dienes (2014) modified an artificial grammar (AG) implicit learning task to incorporate familiar geographical information. The letters strings commonly used in AG tasks were changed to represent flight routes between European cities. The researchers manipulated whether the strings were congruent or incongruent with prior knowledge about distances between cities. Results of the study showed that participants learned more about the artificial grammar structure and applied more prior general knowledge when AG strings violated expectations based on prior knowledge.

Implicit learning research also shows that learners can develop explicit knowledge about complex phenomena, such as artificial grammars and complex sequences, when implicitly learned expectations are violated systematically. In a study employing complex sequences, Rünger and Frensch (2008) found that learners are more likely to be able to report what they have learned in an implicit learning task when they are presented with stimuli that follow a different rule or sequence (as opposed to no rule or a random sequence). Thus, providing stimuli that are incongruent with prior knowledge can lead to explicit knowledge about complex phenomena.

These results have important implications for conceptual change in science learning. First, a typical problem with inducing cognitive conflict is that learners are unaware of their implicit ideas (Limón, 2001). Therefore, learners may lack metacognitive awareness of their prior ideas, making it difficult to demonstrate conflict and induce suppression. Second, learners must be able gather information about new, scientifically accurate structures when their expectations are violated. The findings from implicit learning research suggest that implicit learning tasks may provide opportunities to bring intuitions into awareness, as well as provide opportunities to apply newly-acquired scientific concepts.

In complex science phenomena, while simple rules can often be used to make accurate predictions, novel situations require more sophisticated rules and concepts. Therefore, learners need exposure to novel and varied novel examples to develop a mature understanding of how different variables interact. The above research suggests that for novices, predictions about difficult cases should occur under implicit, rather than explicit, task instructions. That is, the learner's goal should initially be incidental or tangential to the to-be-learned principle or concept. Thus, the pursuit of implicit knowledge in difficult tasks may represent a sort of *desirable difficulty* (Bjork & Bjork, 2011) that can enhance later learning and performance.

In addition to informing conceptual change theory and practice, implicit learning research offers methodological tools for further investigation. Implicit learning tasks such as artificial grammar and process-control tasks provide templates in which to investigate implicit learning in science contexts (see Zimmerman & Pretz, 2012, for example). Likewise, because implicit learning tasks often employ computer-enhanced stimuli and simulations, researchers can gather accuracy and reaction time data to make inferences about the cognitive processes engaged during science learning.

Developing Implicit Learning Tasks for Science

In order to engage students in implicit learning of science concepts, implicit learning task paradigms may be adapted for use with scientific phenomena. Although implicit learning may involve science concepts that do not typically involve misconceptions, this dissertation is particularly interested in describing scientific phenomena about which students typically have intuitions. These tasks should follow three guidelines: *reduce hypothesis-testing strategies, high stimulus volume,* and *bias toward intuitive incongruence.*

First, implicit science learning tasks should reduce the degree to which explicit hypothesis-testing strategies can be employed. That is, tasks should encourage learners to make intuitive decisions. There are several ways to encourage an intuitive approach. One way is the make tasks speeded; by reducing the amount of time learners have to consider stimuli, they are less likely to form conscious rules and gather explicit evidence either confirming or disconfirming those rules. Another way is to reduce the amount of information available. For example, an implicit learning task about motion and forces might provide sparse stimuli without referring explicitly to quantitative variables velocity, mass, friction, and time. This encourages learners to “fill in the gaps” with their intuitive knowledge. On the other hand, a “crowded” task environment can be used to overwhelm perceptual, sensory, and working memory resources. Providing more information than can be actively processed reduces the likelihood that explicit learning will occur.

Second, to capitalize on implicit learning, tasks should expose learners to a high volume of stimuli. Unlike explicit learning tasks, implicit learning tasks involve experience with numerous stimuli. While there are no published guidelines for the number of trials required, research studies typically involve between 25 and 300 trials during a training block.

Third, the stimuli employed in implicit science learning tasks should be biased toward examples that are incongruent with intuitive knowledge. For example, an implicit learning task on the topic of the causes for the seasons on Earth might address the intuition that “closer means strong”—an intuition commonly used by students to support the misconception that the distance between the Sun and Earth is the cause of seasonal temperature differences. To address this intuition, the task should provide many examples of winter / cooler temperatures occurring when the distance between the Sun and Earth is smaller. Biasing tasks towards stimuli that are incongruent with intuitions decreases the likelihood that inaccurate prior intuitions will be reinforced by the task.

General Research Problem

The research problem this dissertation research addresses is how implicit learning can be leveraged to enhance conceptual change in science. In order to address this problem, we developed tasks that employ implicit learning, based on the three guidelines outlined above, in the context of sinking and floating objects in water. The studies in this research provide three unique contributions to the literature on conceptual change.

First, this study applies implicit learning research to explain conceptual change related to why objects sink or float in water. Prior research has shown that students have intuitive ideas about the scientific phenomenon of sinking and floating objects that influence learning of scientific explanations of density (Kloos, Fisher, & Van Orden, 2010; Smith, Carey, & Wiser, 1985). Previous studies have been designed to identify and measure younger students' knowledge of this phenomenon (Schneider & Hardy, 2013; Yin, Tomita, & Shavelson, 2008). In addition, studies have examined the role of instructional scaffolding (Hardy, Jonen, Möller, & Stern, 2006), empirical evidence (Kloos & Somerville, 2001), and scientific discourse (Hardy, Kloetzer, Moeller, & Sodian, 2010) on conceptual change processes related to sinking and floating. Although previous a previous study has addressed how implicit versus explicit processes influence performance on a scientific discovery task related to balance beams (Zimmerman & Pretz, 2013), the role of implicit learning has not been studied in relation to why objects sink and float in water.

Second, this research employed methods for measuring both implicit, intuitive knowledge and explicit, conceptual knowledge of sinking and floating objects. Previous studies have examined implicit, intuitive knowledge (i.e. Kloos, Fisher, & Van Orden, 2010; Potvin, Masson, Lafortune, & Cyr, 2014) or explicit, conceptual knowledge (i.e. Hardy, Kloetzer, Moeller, & Sodain, 2010; Schneider & Hardy, 2013), but not both. Examining learning-induced changes in both intuitive and conceptual knowledge is important for two reasons. First, mature scientific understanding of sinking and floating may be elicited as intuitive or conceptual knowledge. For example, conceptual knowledge about sinking and floating may be demonstrated when a student reproduces the formula for calculating density when interviewed, while intuitive knowledge may be shown when a student applies the heuristics "mass > volume, then sink" and "mass < volume, then float" in a speeded judgment task. Second, the learning progression related to sinking and floating may involve separate changes in intuitive and conceptual knowledge. For example, a person may refine their intuitions about sinking and floating objects by relying on material information to make intuitive judgments. While this person's intuitive knowledge has increased, they could continue lack conceptual knowledge of density necessary for a scientific explanation of why objects sink or float.

Third, the two experiments presented in this dissertation examine the effect implicit learning when leveraged alone (Experiment 1), as well as in combination with direct instruction (Experiment 2). In doing so, this research acknowledges that implicit learning in isolation is not likely to result in conceptual change, at least on a relatively short time scale. On the other hand, the changes induced by implicit learning may enhance learning when combined with other instructional activities. Previous research and theories suggest that combining different learning activities can enhance learning. Hypotheses related to specific theories are tested in Experiment 2 by sequencing implicit learning tasks either before or after direct instruction about density concepts.

Chapter 4: Experiment 1

Experiment 1 was designed to examine whether engaging in implicit learning tasks can effectively influence people's intuitive and conceptual knowledge related to sinking and floating. Training tasks were manipulated to vary the degree to which learning was intentional (i.e., explicit) or incidental (i.e., implicit) in nature. Participants were instructed to make predictions about sinking and floating objects in either an intuitive manner (i.e. quickly, without thinking too much) or an explicit, hypothesis-testing manner. Implicit, intuitive knowledge was measured by examining accuracy and reaction time on a prediction task related to sinking and floating objects. Explicit, conceptual knowledge was measured through assessments designed to elicit misconceptions, reasoning, and understanding of concepts relevant to sinking and floating. Experiment 1 also explored the relationship between these two types of knowledge.

A key finding from research on implicit learning is that incidental forms of training result in improvements in implicit knowledge without corresponding changes in explicit knowledge (e.g., Berry & Broadbent, 1988; Cleeremans, Desdrebecqz, & Boyer, 1998; Lewicki, 1986; Reber, 1989; Seger, 1994; Shanks, 2004). Gains in implicit knowledge are indicated by increased prediction accuracy (e.g., Berry & Broadbent, 1988; Knowlton, Squire, & Gluck, 1994; Reber, 1967) or faster reaction times (e.g. Nissen & Bullemer, 1987; Chun & Jiang, 1998). For the sinking and floating predictions task employed in this research, evidence of implicit learning is indicated by both changes in accuracy and reaction time. Improvements in implicit knowledge in the absence of explicit conceptual knowledge gains may indicate small, but critical progress toward scientific understanding and conceptual change.

Experiment 1 examined the implicit nature of prior intuitive knowledge related to sinking and floating objects. Previous studies show that intuitive science ideas can influence processing speed, even among experts (Goldberg &

Thompson-Schill, 2009; Shtulman & Varcarcel, 2012). That is, people with mature scientific understanding are slower to respond to stimuli that are incongruent with intuitive ideas. The implicit training and assessment tasks used in this research were designed to elicit and challenge prior intuitive ideas about sinking and floating objects by presenting stimuli congruent and incongruent with common intuitions. Differences in accuracy and reaction time for participants' predictions about congruent or incongruent objects provide evidence of the implicit nature of this knowledge. The absence of corresponding changes in explicit conceptual knowledge related to misconceptions would be further indicates that people can learn implicitly about sinking and floating objects.

Although a considerable amount of conceptual change research on sinking and floating objects has been conducted, this is the first experiment, to our knowledge, to examine both implicit and explicit knowledge related to this topic. By measuring both types of knowledge, this experiment offers several empirical insights. First, multiple measures offer a more robust view of people's science knowledge related to sinking and floating. For example, accuracy and reaction time measures of implicit knowledge may reveal subtle changes in knowledge that are not captured in explicit verbal reports. Second, by comparing individuals' performance on implicit and explicit knowledge measures, we have the opportunity to examine the relationship between these types of knowledge. Third, in the context of this experiment, it affords the opportunity to examine how different types of training affect implicit and explicit knowledge.

Research Questions and Hypotheses

The overall goal of Experiment 1 was to examine how implicit learning tasks affect implicit knowledge, explicit knowledge, and the relationship between these two types of knowledge. Experiment 1 addresses three research questions:

RQ 1-1. *How does implicit learning affect intuitive knowledge related to sinking and floating?*

The first hypothesis regarding intuitive knowledge was that participants employ their prior intuitive knowledge about sinking and floating objects to make predictions about sinking and floating objects. Prior intuitive knowledge can positively or negatively affect prediction accuracy depending on whether it leads to predictions that are congruent or incongruent with predictions based on scientific concepts (i.e. density and buoyancy). If participants make predictions based on intuitive knowledge, we expect to see an effect of congruence on prediction performance in the absence of training.

The second hypothesis was that implicit training would result in gains in intuitive knowledge about sinking and floating objects. The effect of training on intuitive knowledge was measured in terms of increased accuracy and faster reaction times on subsequent predictions about sinking and floating objects. We expected that participants in training conditions would make faster and more accurate predictions compared to participants that did not receive training. In order to show that learning was based on transferrable implicit knowledge about sinking and floating objects, and not simply explicit memory for whether particular objects sink or float, we compared performance on objects previously presented during training and novel objects. We predicted that participants in training groups would make more accurate predictions compared to participants without training on both old and novel objects.

The third hypothesis related to this research question was that the effect of training on intuitive knowledge depends on the implicit or explicit nature of learning during the training task. To test this hypothesis, we manipulated the degree of active production during training tasks. Previous research shows that implicit learning is modulated by selective attention (Stadler, 1995; Jiang & Chun, 2001). We predicted that increasing active production would lead to more accurate predictions by increasing attention to relevant information. However, encouraging a rule-testing strategy is also likely to result in slower predictions. Participants that engage in implicit learning processes (i.e. less active production) during training are expected to make faster predictions.

RQ 1-2. *How does implicit learning affect conceptual knowledge related to sinking and floating?*

We hypothesized that implicit learning would not have a significant effect on explicit conceptual knowledge. Several reasons support this hypothesis. First, research on implicit learning has demonstrated that implicit knowledge can be gained in the absence of explicit knowledge (Berry & Broadbent, 1988; Reber, 1967; Nissen & Bullemer, 1987). Second, although the training tasks were designed to elicit and challenge prior intuitive ideas, the brief and speeded nature of these tasks made it unlikely participants would discover the density rule without prior exposure. Third, any gains in explicit knowledge are likely to be small and may not be sufficient for far transfer.

RQ 1-3. *Does training affect the relationship between implicit intuitive knowledge and explicit conceptual knowledge?*

Previous research shows that implicit and explicit knowledge are distinct, yet interacting forms of knowledge (Batterink, Reber, Neville, & Paller, 2015; Berry & Broadbent, 1988; Green & Flowers, 2003; Karmiloff-Smith, 1986; Reber, et al., 1980). Some researchers argue that implicit and explicit knowledge have a positive, synergistic effect on one another (e.g., Mathews, et al. 1989; Rünger & Frensch, 2008; Sun, Mathews, & Lane, 2007). For example, Mathews and colleagues (1989, Experiment 4) found that implicit and explicit knowledge had a synergystic effect on performance on artificial grammar learning task. Other researchers have found that these forms of knowledge can interfere with one another (e.g., Hayes & Broadbent, 1988; Reber, et al., 1980; Ziori, Pothos, & Dienes, 2014). For example, people engaging in explicit learning may develop explicit knowledge of rules that is wrong or incomplete, leading to poorer performance on artificial grammar tasks (Reber, et al., 1980; Experiment 1).

We hypothesize that the relationship between performance on implicit and explicit knowledge assessments will depend on the degree to which training engages explicit knowledge related to sinking and floating objects. For training conditions where participants are encouraged to develop and test explicit rules about sinking and floating, their accuracy on sinking and floating predictions is expected to be positively correlated with conceptual knowledge. That is, if participants make inaccurate sinking and floating predictions based on incorrect rules, they will also be likely to demonstrate inaccurate conceptual knowledge. However, in training conditions that encourage development of intuitive knowledge related to sinking and floating, there is less likely to be a correlation between performance on sinking and floating predictions and conceptual knowledge performance. This is because in implicit forms of training, implicit knowledge of sinking and floating develops independently of explicit conceptual knowledge.

Methods

Design

This study employed a mixed-effects design. The between-subjects factor was training condition with 4 levels –*explicit training*, *implicit training*, *incidental training,* and *no training*. For sinking and floating performance, there were two within-subject factors—congruence and new/old—with two levels each. In addition, the effects of training on explicit conceptual knowledge were explored by examining performance on conceptual knowledge assessments.

Participants

To determine adequate sample sizing for the experimental design, a power analysis was conducted, following recommendations from Guo, Logan, Glueck, & Muller (2013). Data from a previous study (Wang, Varma, & Varma, 2012) was analyzed to estimate variance and effect size inputs. The GLIMMPSE program (http://glimmpse.samplesizeshop.org/) was used to calculate sample sizes. Using a clustering of 50 trials per participant and an intra-cluster correlation of 0.03, the model above was specified for accuracy response data with a mean difference of

0.1 among conditions. The analysis employed the Hotelling-Lawley Trace statistical test, with a Type I error rate of .05. Variability of within-participant factors was estimated at 0.6 and variability across responses was estimated as 0.3. The results of the analysis showed that a total sample size of 60, with 15 participants in each group would yield power of β = .806.

Fifty-six participants (*M* age = 20.3, 48 female) were recruited from the University of Minnesota via class announcements and recruitment postings. Participants were compensated with course credit or a $10 gift card. Participants were tested individually in a lab room. Sessions lasted approximately 45 minutes. The experimental protocol was approved by the Institutional Review Board of the University of Minnesota.

Materials

Prior knowledge assessment. Before beginning the training phase, each participant was asked to answer the following question: "Do you know of a rule, or set of rules, that can be used to determine whether an object will sink or float in water?" Responses to this question were used to determine baseline knowledge about the causes of sinking and floating. This assessment was also used to identify participants likely to perform at ceiling across the implicit and explicit knowledge assessments.

Training tasks. In the training task, participants were presented with various objects and asked to predict whether each object would sink or float in water. The objects varied in material (clay, iron, wax, or wood), shape (cube, sphere, tetrahedron, or flat), size (small, medium, large), holes (holes or no holes), and hollowness (hollow or not hollow). A picture of the object was presented along with an image of a hand or person to provide scale. A table summarizing the object's characteristics appeared along with the picture (see *Figure 4.1*). This table included information about the object's mass (g) and volume (ml) when submerged, allowing participants to calculate and apply the density concept to make the predictions (i.e. objects with density greater than the density of water, 1 g/ml, sink, and objects with density less than water float). Participants responded by pressing a corresponding button on a keyboard ('Q' for sink and 'P' for float). After each responding, participants were shown a feedback screen for 1500 ms. This screen provided feedback on accuracy (green screen with "CORRECT" or red screen with "INCORRECT"), as well as response time.

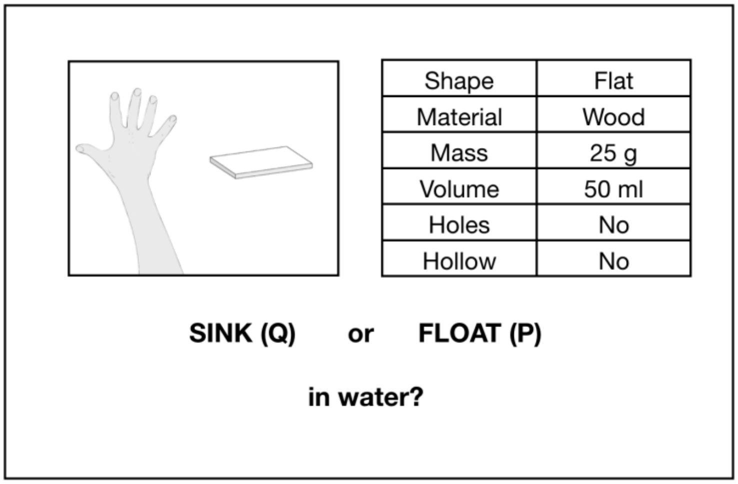


Figure 4.1. Example of stimuli presented in training and test trials

Inhibition ability assessments. Inhibitory mechanisms may play an important role in suppressing intuitive, incorrect responses and reasoning related to science and math concepts (Babai et al., 2012; Foisy et al., 2015; Potvin et al., 2014). Thus, increased inhibition ability may reduce the effect of training. To account for individual differences in inhibition ability, all participants completed two assessments of inhibition ability—the Dimensional Change Card Sort task (DCCS; Zelazo, 2006) and Flanker task (Eriksen & Eriksen, 1974)—before and after the training phase, respectively. In the DCCS, participants sort objects based on a shape or color rule, switching between rules throughout the task. In switching between rules, participants must inhibit the previous rule and the dimension associated with it (i.e. the color or shape of the object). In the Flanker task, participants are presented with a row of several arrows and their task is to determine the direction the center arrow is pointing (left or right). The stimuli vary as to whether the surrounding arrows are in the same or opposite direction of the middle arrow. Therefore, when the surrounding arrows are in the opposite direction, the task requires inhibition of these stimuli to make an accurate response. For each measure, a score is calculated based on accuracy and reaction time on target trials (post-switch or incongruent, respectively). Scores from each measure were added together to produce a single inhibition ability score. Inhibition ability measures were included as covariates to control for individual differences.

Sinking and floating prediction task. Intuitive knowledge was assessed by examining participants' predictions about sinking and floating objects. The presentation of each object was identical to the training phase, except that feedback was not provided. During this phase, 28 items had been previously presented during training, and 22 were new. Of the old items, 3 were repeated during the test, which provided an opportunity to check if participants responded consistently across items. Objects were presented in a random order for each participant. In contrast to the training phase, no feedback was provided.

Across both training and test phases, a larger proportion of incongruent objects were presented. This was intended to increase the difficulty of the task, as well as activate intuitions about sinking and floating objects. Across all trials, 89% of trials were congruent with material-based intuitive rules ("wood objects float" "iron objects sink"), and 63% of trials were congruent with intuitive rules about size ("larger objects sink" "smaller objects float"). For the 23% of trials that were flat-shaped, the intuitive rule "flat object float" was accurate 46% of trials. For trials that included objects with holes (23% of trials), the intuitive rule "objects with holes sink" led to accurate predictions 65% of the time. Similarly, the intuitive rule "hollow objects float" led to accurate predictions 65% of the time for trials that had hollow objects (36% of trials).

Conceptual knowledge test. Participants completed an assessment of conceptual knowledge related to sinking and floating objects (see Appendix A for assessment items). Items were adapted from assessments designed to identify students' misconceptions about sinking and floating (Edelsbrunner, Schalk, Schumacher, & Stern, 2015; Yin, Tomita, & Shavelson, 2008). The assessment required students to make sinking and floating predictions about objects in various scenarios. These items did not require calculation of density. Rather, they were designed to elicit misconceptions about sinking and floating objects. For example, two round spheres, one solid and one hollow, are shown together; the objects are described as having the same density and that the solid object sinks. The participant selected one of the following 3 responses in relation to the hollow object: sink, float, or neither sink nor float. Participants also provided reasoning for their answers in written form to potentially provide insight into participants' explicit thinking about each item.

In addition, participants were asked to rate their agreement with 10 statements related to sinking and floating objects on a 5-point Likert-type scale from "Agree" to "Disagree." The statements were chosen to reflect intuitive beliefs about sinking and floating objects, for example, "Heavy objects always sink" and "Hollow objects always float" (see Appendix A for full list of statements).

Finally, participants responded to the same open-ended prompt presented at the beginning of the session asking them to describe a rule or set of rules for determining sinking and floating. The conceptual knowledge assessment was administered on a computer using Qualtrics survey software.

Procedure

All participants began the procedure with the prior knowledge assessment. This was followed by the Flanker task. This task served the additional role in providing a delay between assessment of prior knowledge and the training phase to decrease the likelihood of information about sinking/floating rules and/or associations for individual objects being recalled from working memory.

Training phase. Participants were randomly assigned to one of the four conditions: *explicit training, implicit training, incidental training,* or *no training.* The sequence of objects used in the training phase was based on performance data from a previous study (Wang, Varma, & Varma, 2012). After 10 trials that conveyed the range of materials, shapes, and sizes to expect, each subsequent set of 10 objects were designed to elicit and challenge intuitions about sinking and floating objects. For example, in a set that elicited the intuition "large objects sink," several objects congruent with this intuition (i.e. large, sinking objects) were presented, followed by objects incongruent with this intuition (i.e. large, floating objects). The order of congruent (C) and incongruent (I) objects in relation to each intuition followed the pattern: C, C, C, I, C, C, I, C, I, I. The other intuitive ideas activated were: “small objects float,” “objects with holes sink,” and “hollow objects float.”

Participants assigned to the *explicit training* condition were instructed to “search for a rule or set of rules that could be used to make sinking and floating judgments.” In the *implicit training* condition, participants were instructed to “make judgments as quickly as possible without thinking too much. Just trust that your performance will improve over time” (directions adapted from Zimmerman & Pretz, 2013).

The *incidental training* condition tested whether mere exposure to sinking and floating object associations would improve performance. The training task in this condition consisted of the same 50 objects presented in the *implicit* and *explicit training* conditions. However, instead of making predictions, the participants’ task was to “remember as many objects as possible.” After a fixation period of 1500 ms, each object was displayed with the word “SINK” or “FLOAT” below the object picture and object information table; each object was displayed for 4000 ms. While each object was displayed, the participant was required to press the ‘S’ key if the display contained the word “SINK”; no action was taken if the screen displayed “FLOAT.” The purpose of this task was to ensure that the participant paid attention to the sinking and floating information for each object throughout the sequence.

Participants in the *no training* condition did not complete the training task, though they participated in cognitive assessment and intuitive and conceptual knowledge assessment tasks. The 4 conditions—*explicit training, implicit training, incidental training,* and *no training*—were treated as a between-subjects factor.
After completing the specified training task (or lack thereof), the participants completed the Dimensional Change Card Sort task to increase the likelihood that knowledge gained from training would be recalled from long-term, rather than working memory.

Testing phase. In the testing phase, participants were given two assessments, the sinking and floating prediction task designed to capture intuitive knowledge, and the conceptual knowledge test. For each participant, the implicit knowledge assessments were presented first, followed by the explicit knowledge assessments. This was done to avoid possible testing effects related to explicit knowledge assessments.

In this sinking and floating task, reaction time and prediction accuracy were recorded for each trial. In addition, objects were analyzed based on whether or not they violated intuitive rules about sinking and floating (i.e., 'larger objects sink,' 'smaller object float,' 'objects with holes sink,' and 'hollow objects float'). In order to analyze intuitive responses, objects that violated one or more intuitive rules were labeled "Incongruent"; objects that did not violate intuitive rules were labeled "Congruent." Object congruence with intuitive rules was analyzed as a between-subjects factor.

Debriefing interview. Following all computer-based tasks, participants answered questions in an interview conducted by the researcher. Participants described the strategies they used to make sinking and floating predictions, including what information they focused on during the task. If a strategy wasn't spontaneously described, participants were prompted to explain whether they used information on the left (object image) or right (object information table) of the screen when making their predictions. This information was used to determine if the participant employed the density rule (i.e. mass greater than volume = sink; mass less than volume = float). Participants were also asked if they felt that they learned something from the tasks, and if so, whether they could put what they learned into words. This information was used to determine whether they learned the density rule during the task or previously learned the strategy.

Results

Training task performance. Prior to analysis, accuracy and reaction time data was inspected to identify outliers. One participant in the *incidental training* condition reported not following directions correctly for part of the training task, which was confirmed by a low accuracy score (*M* accuracy = .52 vs. group *M* accuracy = .99). Data from this participant was removed from further analysis of training data.

To confirm that training manipulations were effective, a 3 x 2 mixed ANCOVA was conducted on accuracy data, with a between-subjects factor of Training with 3 levels (*explicit, implicit,* and *incidental training*) and a within-subjects factor of Congruence with two levels (congruent, incongruent), and inhibition ability score as a covariate to control for individual differences. This analysis revealed main effects of Training condition (F (2, 37) = 18.060, p < .001, η^2 = 0.348) and Congruence (F (1, 37) = 11.080, p = .002, η^2 = 0.119). These main effects were qualified by a significant two-way interaction between Training and Congruence (F (2, 37) = 3.253, p = .050, η^2 = 0.074). Visual examination of plots showed that the effect of Congruence was larger in the *implicit training* condition (congruent *M* = .92 vs. incongruent *M* = .84) than in the *explicit training* condition (congruent *M* = .95 vs. incongruent *M* = .90). In the *incidental training* condition, accuracy across congruent and incongruent was equivalent (congruent *M* = .99 vs. incongruent *M* = .99). The accuracy data results are summarized in Figure 4.2 (top).

These results provide evidence of the effectiveness of the task manipulations. The *implicit training* condition was designed to engage participants' intuitive knowledge. The increased effect of Congruence is evidence that participants in the *implicit training* condition were more likely than participants in the *explicit condition* to rely on prior intuitive knowledge about sinking and floating to make their predictions. The lack of effect of Congruence in the *incidental training* condition was expected, as this condition did not require making predictions (all answers were given on the screen).

Analysis of reaction time data provided further confirmation of training manipulations. Prior to analyzing reaction time data, RTs were trimmed and transformed following guidelines outlined by Whelan (2008). To minimize effects of outliers, large RTs were truncated to 8000 ms, approximately 3 standard deviations above the mean. This resulted in < 1% of observations being truncated. To maintain power, RTs were subjected to log transformation prior to analysis. Also, RT data analyzed for the *incidental training* condition were only from trials that required a response (no response trials did not register RTs).

Training reaction time data was analyzed using a 3 x 2 mixed ANCOVA, with a between-subjects factor of Training condition with 3 levels (*explicit, implicit,* and *incidental*) and a within-subjects factor of Congruence with two levels (congruent, incongruent). Inhibition ability score was included as a covariate in the model to control for individual differences. This analysis showed main effects of Training (F (2, 37) = 5.317, p = .009, η^2 = 0.212) and Congruence (F (1, 37) = 10.892, p = .002, η^2 = 0.018). The main effects were qualified by a significant two-way interaction between Training and Congruence (F (2, 37) = 9.326, p < .001, η^2 = 0.030). Post-hoc analyses of comparisons with adjusted p-values showed that the effect of Congruence was greatest for the *explicit training* condition. In this condition, RTs on congruent trials were significantly longer than on incongruent trials (p < .001). Differences between congruent and incongruent trials in the *implicit* and *incidental* training conditions were not significant (ps > .075).

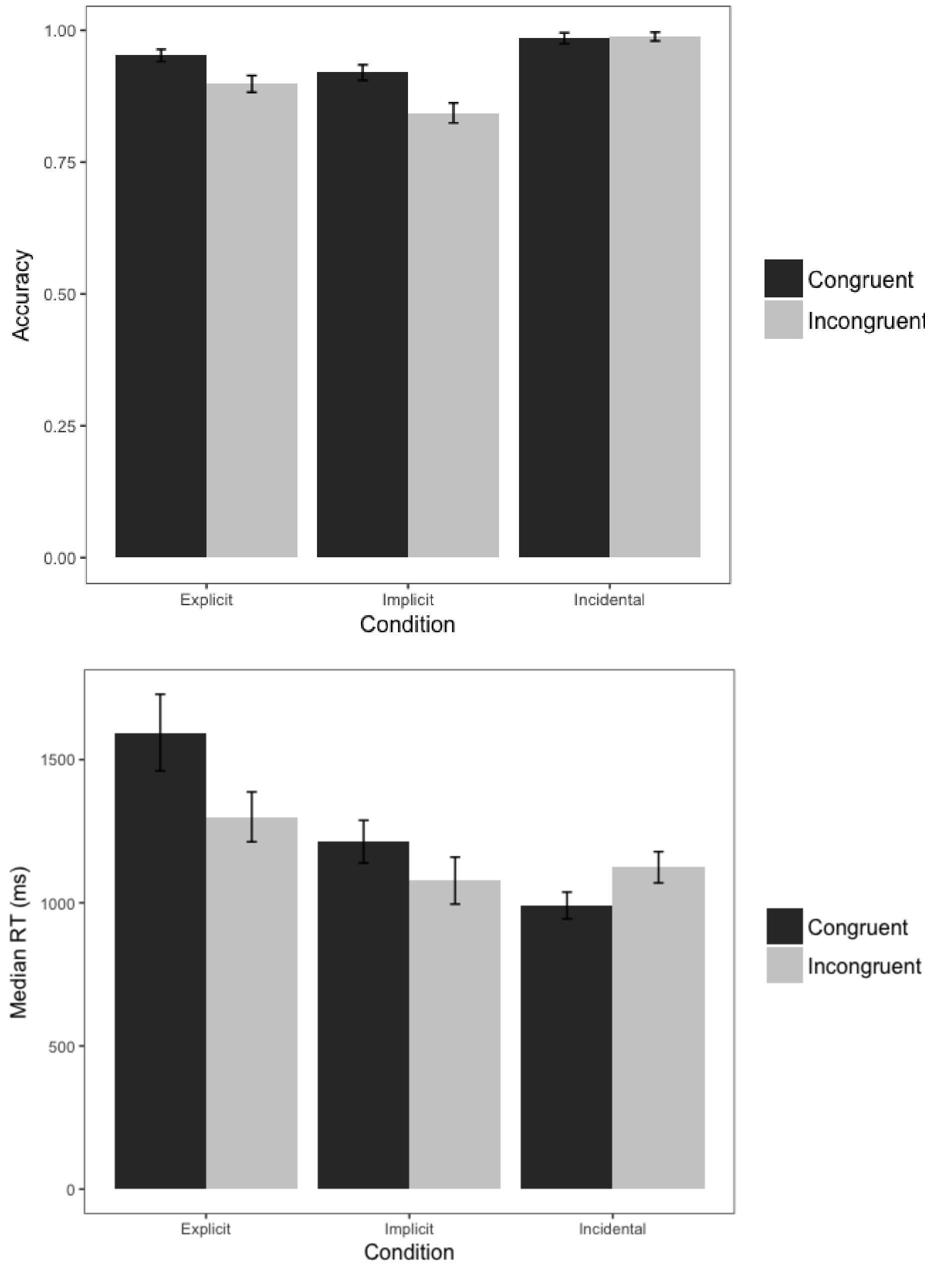


Figure 4.2. Training task performance for Experiment 1. Accuracy (top) and median RT (ms) (bottom) for each group, separated by congruence.

These results provide further evidence that manipulations to training task instructions were effective. Increasing the degree active production led to slower predictions in the in the *explicit training* condition compared to the more passive conditions. The effect of Congruence in the *explicit training* and *implicit training* conditions showed that predictions were faster for incongruent trials, suggesting that participants relied on intuitive knowledge when making predictions in these conditions. Interestingly, the effect of Congruence was opposite for the *incidental training* condition: responses on incongruent trials were slower than congruent trials. This may have been due to participants being slowed down when making responses conflicting with their expectations based on intuitive knowledge. It is possible that participants in this condition, while not required to actively make predictions, did so anyways, providing evidence of implicit learning in this condition.

Sinking and floating prediction task performance. To examine the effect of training on intuitive knowledge (RQ 1-1), a 4 x 2 x 2 mixed ANCOVA was conducted on sinking and floating prediction accuracy data, with a between-subjects factor with 4 levels (Training: *no training, explicit, implicit*, and *incidental*), and 2 within-subjects factors with 2 levels each (Congruence: congruent or incongruent; Novelty: new or old). Inhibition ability score was included as a covariate to control for effects of individual differences. The results of this analysis showed significant main effects of Training ($F(3,52) = 5.486$, $p < .001$, $\eta^2 = 0.169$) and Congruence ($F(1,52) = 72.160$, $p < .001$, $\eta^2 = 0.223$). These main effects were qualified by a significant two-way interaction of Congruence by Novelty ($F(1, 52) = 7.952$, $p = .007$, $\eta^2 = 0.013$).

Post-hoc pairwise analysis, with Bonferroni adjustment of *p*-values, showed the main effect of Training on accuracy was driven by the *no training* condition ($M = .64$, $SE = .02$) being significantly less accurate than each of the other Training conditions (*p*s < .001). This result supports the hypothesis that training results in gains in implicit knowledge. Analysis of the Congruence by Novelty interaction showed that the effect of Congruence was greater within new trials than old trials. New, incongruent trials ($M = .70$, $SE = .02$) were less accurate than old, incongruent trials ($M = .76$, $SE = .02$) ($p = .018$). However, for congruent trials, there was no significant difference between old and new trials ($p = .305$). That is, participants in training conditions transferred implicit knowledge better on congruent trials than on incongruent trials. This suggests that the implicit knowledge gained through instruction was more helpful on congruent than on incongruent trials. Accuracy data is summarized in Figure 4.3.

Analysis of reaction time data provided further evidence for the effect of training on intuitive knowledge (RQ 1-1). Prior to conducting the analysis of reaction times, data was trimmed and transformed following guidelines outlined by Whelan (2008). To minimize effects of outliers, large RTs were truncated to 8000 ms, approximately 3 standard deviations above the mean. This resulted in < 3% of observations being truncated. To maintain power and better meet assumptions of statistical models, RTs were subjected to log transformation prior to analysis.

A 4 x 2 x 2 repeated-measures ANCOVA was conducted on the log-transformed RTs, with Training condition (4 levels) as a between-subjects factor, Congruence (congruent/incongruent) and Novelty (old/new) as within-subjects factors, and inhibition ability score as a covariate. This analysis showed significant main effects of Training ($F(3, 52) = 16.425$, $p < .001$, $\eta^2 = 0.458$), Congruence ($F(1, 52) = 23.122$, $p < .001$, $\eta^2 = 0.016$), and Novelty ($F(1, 52) = 8.253$, $p = .006$, $\eta^2 = 0.006$). These main effects were qualified by two significant two-way interactions: one for Training by Congruence ($F(3, 52) = 7.144$, $p < .001$, $\eta^2 = 0.014$), and another for Congruence by Novelty ($F(1, 52) = 10.523$, $p = .002$, $\eta^2 = 0.006$).

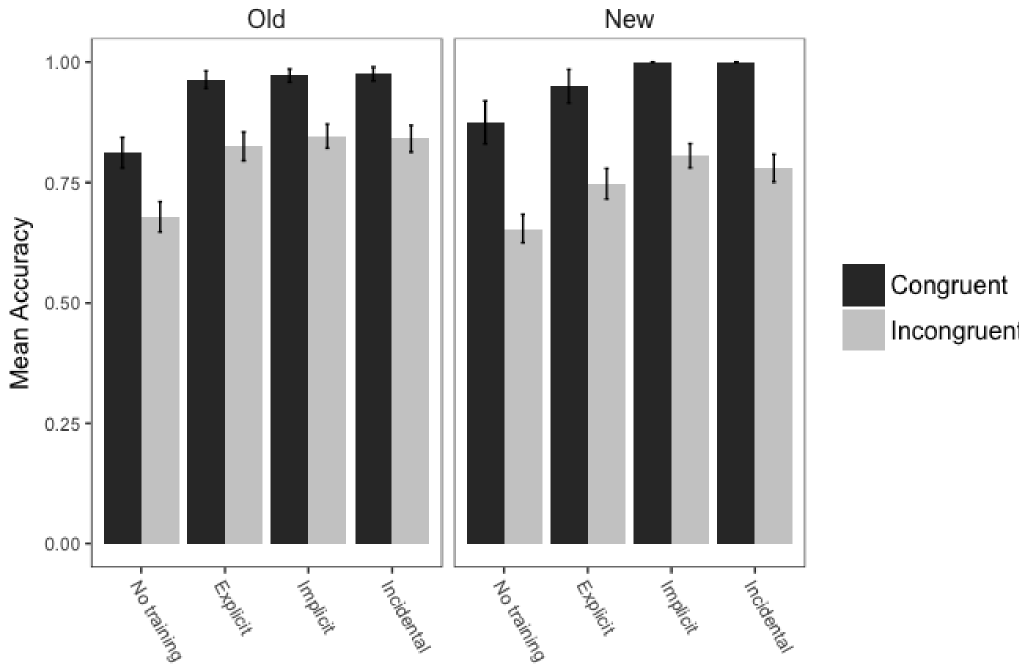


Figure 4.3. Accuracy on sinking and floating prediction task for Experiment 1.

Pairwise comparisons, with Bonferroni adjustment to *p*-values, were analyzed for the main effects on RT. Analysis for the main effect of Training showed that trials in the *no training* condition were significantly longer than each of the other conditions (all *p*s < .001). The main effect of Congruence was due to congruent trials being significantly shorter than incongruent trials ($p < .001$). Together, these main effects support the hypothesis that training results in implicit learning related to sinking and floating by demonstrating a facilitative effect to processing. The main effect of Novelty showed that new trials were significantly slower than old trials ($p < .001$), suggesting that memory for objects presented in training (whether implicit or explicit) facilitated responses.

The two-way interactions qualifying these main effects provide further support of hypotheses and details related to RQ 1-1. Pairwise analysis (with Bonferroni-adjusted p-values) for the 2-way interaction between Congruence and Novelty showed that new, incongruent trials were the slowest in comparison to the other types of trials (*p*s $< .05$). Thus, knowledge gained from training does not transfer to new situations where intuitive and scientific rules are incongruent. The interaction between Congruence and Training showed that the effect of Congruence varied by Training. The effect of Congruence was strongest in the *implicit training* condition; within this condition, incongruent trials were significantly longer than congruent trials ($p < .001$). This difference can be interpreted as indication that participants in this condition gained implicit knowledge of the difference between trials where intuitive knowledge is helpful and when it is not. That is, participants in the *implicit training* condition learned to recognize and slow down (i.e. suppress) their intuitions that might lead to incorrect predictions.

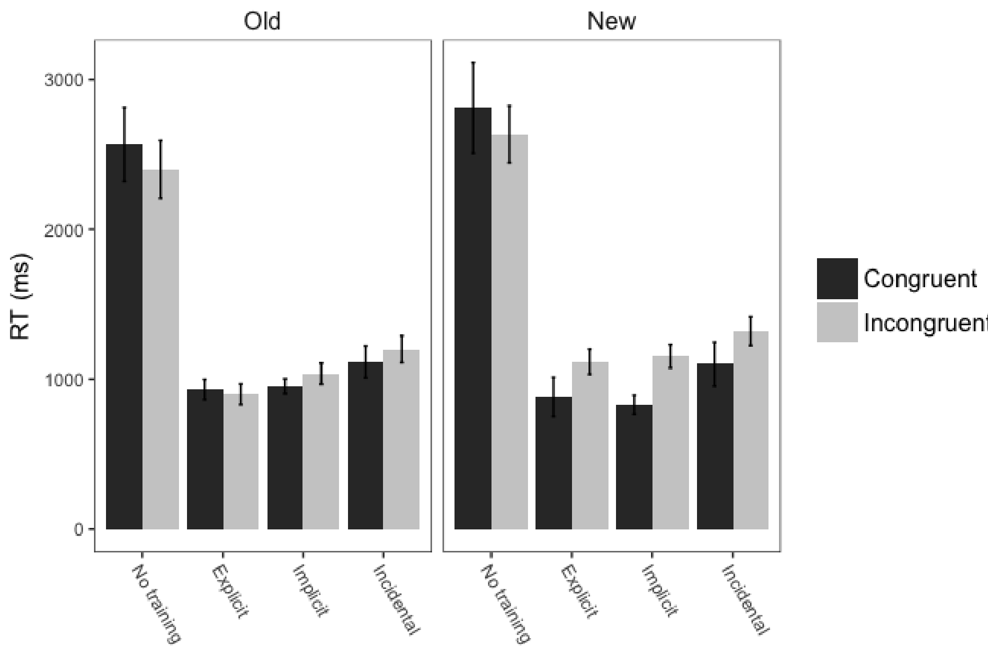


Figure 4.4. Reaction times on sinking and floating prediction task for Experiment 1. Median RTs with standard error of medians for congruent and incongruent trials across training conditions.

Conceptual test measure. The 12 selected response items were scored 0 (incorrect) or 1 (correct). Responses to the written reasoning prompts on the 10 conceptual knowledge items were rated on a scale of 0 to 2 points, according to a rubric measuring density reasoning (see Appendix B for rubric). Ratings were made by the researcher and an additional rater blind to experimental conditions. There was a satisfactory level of agreement between raters (Cohen's kappa = .698, $p < .001$) and disagreements were resolved through discussion. The test of conceptual knowledge had high reliability (Cronbach's α = .88). A total of 32 points were possible on the test, 12 points from selected answers, 20 points from written responses of reasoning. The mean score was 21.15, with a range of 4.75 to 32 and a standard deviation of 7.13. A summary of the results of the conceptual assessment is provided in Table 4.1.

Table 4.1

Summary of Conceptual Test Measures for Experiment 1

	Training Condition					
	No Training *n= 15*	Explicit *n= 14*	Implicit *n= 14*	Incidental *n= 13*		
	Mean (SE)	*Mean (SE)*	*Mean (SE)*	*Mean (SE)*	$F(3,52)$	p
Selected Response	9.0 (0.6)	9.1 (0.6)	9.5 (0.5)	9.3 (0.6)	0.175	.913
Written Reasoning Prompts	9.9 (1.5)	12.9 (1.5)	12.6 (1.3)	12.5 (1.6)	0.092	.438
Total	18.9 (2.0)	21.9 (1.9)	22.1 (1.7)	21.9 (2.1)	0.674	.572

To determine the effect of training on explicit conceptual knowledge (RQ 1-2), scores on the conceptual test measure were analyzed using two-way ANOVAs with Training as a between-subjects factor. Comparisons of scores across training conditions did not reveal a significant effect of Training on scores for selected response items, written reasoning prompts, or on total score (see Table 4.2 for statistical test results). This supports the hypothesis that the implicit training employed in Experiment 1 would not have a corresponding effect on conceptual knowledge.

Table 4.2

Pre-Post Explicit Knowledge Assessment Results for Experiment 1

	Training Condition					
	No Training *n*= 15	Explicit *n*= 14	Implicit *n*= 14	Incidental *n*= 13		
	Mean (SE)	*Mean (SE)*	*Mean (SE)*	*Mean (SE)*	*H*(3)	*p*
Pre	1.87 (0.35)	2.36 (0.37)	1.79 (0.42)	2.31 (0.26)	2.208	.530
Post	2.07 (0.37)	2.79 (0.37)	2.43 (0.34)	2.23 (0.23)	2.469	.481
Change Pre-Post	0.20 (0.24)	0.43 (0.20)	0.64 (0.25)	-0.08 (0.26)	4.486	.214

Pre-post explicit knowledge assessment. Responses to the free response prior knowledge prompt were rated according to a rubric ranging from 0 to 5 points, reflecting knowledge of the density rule (0 = no knowledge, 5 = mature scientific knowledge of density, see Appendix C for rubric and examples). A rating of 2 or higher indicated that the participant mentioned "density" in their response; a rating of 4 or higher indicated an accurate description of the definition of density (ratio of mass to volume). Responses were coded by the researcher and a rater blind to experimental manipulations. There was a satisfactory level of agreement between raters (Cohen's kappa = .701, $p < .001$ across all ratings) and disagreements were resolved through discussion. Across groups, the mean prior knowledge rating was 2.09 (SE = 0.2). A Wilcoxon Signed-Ranks Test indicated that pre-post changes across all participants were greater than 0, $Z = 322.5$, $p < .001$. The data from the pre-post assessment are summarized in Table 4.3.

Table 4.3

Agreement Ratings with Intuitive Statements for Experiment 1

	Training Condition				
	Direct	Implicit+Direct	Direct+Implicit	*H*(2)	*p*
Inaccurate intuitive rules					
"Objects with holes always sink"	3.92 (0.34)	4.25 (0.49)	4.20 (0.36)	0.57	.75
"Hollow objects always float"	3.83 (0.42)	3.50 (0.50)	4.10 (0.35)	0.29	.86
"Heavy objects always sink"	4.58 (0.34)	3.37 (0.56)	4.40 (0.40)	2.58	.27
"Light objects always float"	4.25 (0.35)	3.63 (0.68)	4.10 (0.46)	0.54	.76
"Large objects always sink"	4.50 (0.34)	4.50 (0.38)	4.70 (0.15)	0.02	.99
"Small objects always float"	4.91 (0.08)	4.50 (0.38)	4.90 (0.10)	3.11	.21
"Objects made of iron always sink"	3.08 (0.58)	2.75 (0.62)	2.70 (0.58)	0.05	.97
"Objects made of clay always sink"	4.58 (0.26)	4.00 (0.38)	3.60 (0.52)	1.83	.40
Accurate intuitive rules					
"Objects made of wood always float"	2.58 (0.45)*	3.75 (0.52)*	3.00 (0.58)	6.73	.03*
"Objects made of wax always float"	2.67 (0.59)	3.75 (0.45)	3.40 (0.50)	1.97	.37

Ratings are coded with ‘1’ as ‘agree’ and ‘5’ as ‘disagree.’ Non-parametric statistical tests (Kruskal-Wallis and Wilcoxon tests) were used to analyze differences across conditions. Statistically significant differences are noted with a * $p < .05$.

To address whether training had an effect on explicit knowledge about sinking and floating (RQ 1-2), pre, post, and change scores were compared across Training conditions. Based on a non-parametric analysis of variance (Kruskal-Wallis test), there were no significant differences across groups (see Table 4.2 for statistics). This suggests that training did not affect explicit knowledge about sinking and floating. However, power analysis showed that this measure may have been underpowered, so this interpretation should be accepted with caution.

Non-parametric ANOVAs (Kruskal-Wallis tests) were conducted for responses to each statement, as examination of the distribution of ratings showed that they were skewed. These analyses revealed significant differences in agreement ratings across Training conditions found for three intuitive statements. Participants in the *explicit* condition were more likely than those in the *no training* condition to disagree with the statement “Objects with holes always sink” (H (3) = 11.57, p = .01; U = 106.5, p = .005). Participants in the *implicit training* condition showed more agreement than those in the *no training* condition to the statement

“Objects made of wood always float” ($H(3) = 7.880$, $p = .05$; $U = 27.5$, $p = .008$). Finally, for the intuitive statement “Objects made of wax always float,” participants in the *no training* condition had significantly higher disagreement ratings than for all other conditions (*p*s < .05). In these latter two cases, a lower number (indicating greater agreement) with the intuitive rule was more accurate.

Relationship between performance on prediction task and conceptual assessment. To examine the effect of training on the relationship between different types of knowledge (RQ 1-3), the correlations between prediction accuracy and conceptual test scores were calculated for each group. Rank-ordered correlations were calculated (Kendall’s τ) to avoid violating assumptions of normality. The correlations between performance on sinking and floating predictions and the conceptual test for the *no training* and *explicit training* conditions were strong, positive, and significant (*p*s < .01). The correlations for the *implicit training* and *incidental training* conditions were not significant. The correlation and significance statistics are presented in Table 4.4; the data is summarized graphically in Figure 4.5.

These results suggest that training tasks that improve performance in an implicit or incidental manner do so based on intuitive knowledge gains and not conceptual knowledge. The strong correlation between scores in the *explicit training* condition suggest that improvements in the sinking and floating prediction task were based on increased explicit knowledge of rules governing sinking and floating.

Table 4.4.

Kendall's Rank Correlations between Conceptual Test Scores and Sinking and Floating Prediction Task Accuracy for Experiment 1

Condition	τ	*p*
No Training	.54	.006*
Explicit Training	.65	.002*
Implicit Training	.35	.09
Incidental Training	.16	.45

* $p < .05$

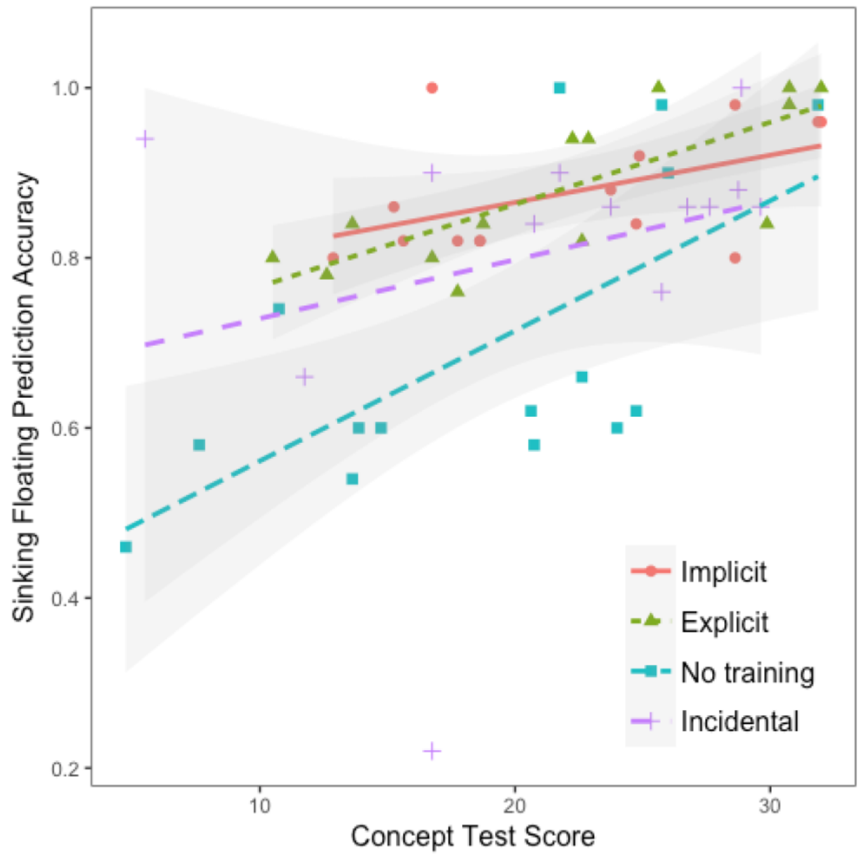


Figure 4.5. Relationship between conceptual test score and sinking and floating prediction task accuracy by Training condition for Experiment 1.

Discussion

The results of Experiment 1 provide evidence that learning related to scientific phenomena occurs in tasks designed to engage implicit learning processes. Following training, participants in the *explicit, implicit,* and *incidental* training conditions showed improved performance in predicting whether objects sink or float in water—their predictions were more accurate and faster.

Further evidence of learning comes from performance on trials where new objects (i.e. not present during training) were presented; participants in the 3 training conditions made more accurate predictions about novel objects than participants in the *no training*. Thus, participants were able to extract and transfer information about objects that was used to make more accurate predictions about new objects. If participants had simply memorized correct answers from training trials, we would expect to see (a) similar performance on new items by participants in the 3 training conditions as those in the *no training* condition, and (b) similar performance across congruent and incongruent old items. Further, improved performance on new, incongruent items suggests that these participants learned something about objects that violate intuitive rules. That is, improvement across both congruent and incongruent new trials (approximately 10% and 20% respectively) suggests that participants in training conditions did not simply reinforce and apply intuitive rules.

Although participants in the *incidental training* condition were required to respond with a button press (or no button press), this task did not require the generation of predictions prior to receiving correct information about sinking and floating object. Their performance provides evidence that learning can occur in a relatively passive manner. This is supported by the faster RTs for training trials in the *incidental training* condition as compared to training trials in the *explicit* and *implicit training* conditions. If participants in this condition generated predictions prior to responding, we would predict longer RTs compared to those in *implicit training* on incongruent trials during training.

More generally, the approximately equivalent performance, in terms of prediction accuracy, across *explicit, implicit,* and *incidental* training groups suggests the learning that occurs during these tasks is roughly equivalent. Thus, the improved performance across each of these groups is not influenced by the two key manipulations to the training task: whether participants are told to explicitly search for a rule governing sinking and floating object or not, and whether a prediction was generated or not. Although the most parsimonious explanation for the roughly equivalent accuracy gains is that these manipulations do not differentially affect learning, there was evidence for subtle, yet important, differences in the learning that results from each of the training conditions.

First, in the intuitive rules task, participants in the *explicit training* condition were more likely to reject the intuitive rule *"Objects with holes always sink"* compared to *no training* controls. A hypothesis-testing strategy might account for this result; attending to data that contradicts a rule leads to rejection of that rule. On the other hand, participants in the *implicit training* condition were more likely to agree with the intuitive rule *"Objects made of wood float."* While intuitive, this statement is also scientifically accurate (not taking into account wood type and water absorption). This supports the argument that those in the *implicit training* condition were more likely to learn an intuitive rule.

The other notable result from the sinking and floating prediction task results was that for the *implicit training* condition, incongruent trials were slower than congruent trials. To put this in context, consider a participant in the *implicit training* encountering a hollow object that sinks (i.e., incongruent with the intuitive rule *"hollow objects float").* Before training, they responded to these types of trials faster than compared to those that were congruent with intuitive rules. However, after training, they took more time to make these predictions. There are at least two possible explanations for the observed difference in RTs between congruent and incongruent trials for participants in the *implicit learning* condition.

One interpretation is that participants in the *implicit learning* condition may have learned how to better apply intuitive rules to congruent trials. Thus, congruent trials were faster than incongruent trials because using these rules requires less cognitive processing. For example, if people use the intuitive rule *"hollow objects float,"* then we would expect people to respond faster to items that are hollow. Analysis of RTs in the *no training* condition showed similar median RTs for hollow and non-hollow object.

A second interpretation is that slower RTs during incongruent trials are the result of a cognitive "pause" during trials that violate intuitive sinking and floating rules. That is, through training participant learn to recognize trials that do not follow intuitive rules. Put another way, participants in the *implicit training* condition not only learned how to associate characteristics that reliably predict sinking and floating objects, they also learned which intuitive association were unreliable. This interpretation is in line with research demonstrating that developing science understanding involves the suppression of intuitive ideas (Shtulman & Varcarcel, 2012; Masson, Potvin, Riopel, Foisy, 2014).

Results from this experiment also show that while there is a positive correlation between intuitive and conceptual knowledge without training, this relationship does not hold when training occurs. That is, participants gained knowledge to better predict whether objects sink or float in water, however, they did not make similar gains in their explicit conceptual knowledge.

Although the implicit learning task did not result directly in conceptual learning, it is possible that improved intuitive knowledge, indicated by both the activation of accurate intuitions and suppression of inaccurate intuitions, may enhance opportunities to gain conceptual knowledge (Bransford & Schwartz, 1999; Schwartz & Bransford, 1998; Schwartz & Martin, 2004; Schwartz & Martin, 2010). The relationship between intuitive and conceptual knowledge is further explored in Experiment 2 by examining how directly presenting conceptual knowledge to participants influences both their intuitive and conceptual knowledge.

Chapter 5: Experiment 2

Building on Experiment 1, Experiment 2 explores the general hypothesis that the implicit knowledge gained through implicit training activities can promote explicit knowledge when combined with direct instruction. In typical science classroom instruction, students gain explicit knowledge of concepts through direct instruction. Direct instruction involves presenting overt descriptions and explanations of concepts, relationships, and rules underlying observable scientific phenomena or examples (e.g., Chen & Klahr, 1999; Klahr & Nigam, 2004; Schwartz & Martin, 2004). Experiment 2 employs a video representation of typical direct instruction related to sinking and floating. This video was presented to participants in combination with the implicit training task from Experiment 1 to test the hypothesis that refining implicit knowledge can improve explicit knowledge gained from direct instruction.

Another important consideration for learning is the *sequencing* of instructional activities designed to promote implicit and explicit knowledge. There may be an advantage to developing implicit knowledge before gaining explicit knowledge through direct instruction; conversely, having explicit knowledge before implicit training learning activities may be more effective. There is empirical and theoretical support for both possible sequences. For example, Mathews and colleagues (1980, Experiment 4) found that optimal learning of a simplified (biconditional) artificial grammar occurred when an implicit knowledge base was developed before generating explicit knowledge. Sequencing implicit learning before explicit learning is supported by theories that suggest that explicit knowledge develops from implicit knowledge (e.g., Dienes & Perner, 1999; Karmiloff-Smith, 1986; Rünger & Frensch, 2008). On the other hand, Reber and colleagues (1980, Experiment 2) found that providing explicit information about underlying rules of an artificial grammar prior to an implicit learning task improved subsequent ability to discriminate between grammatical and non-grammatical strings.

Theory and evidence from science education research is also informative on the matter of sequencing. There are at least three reasons why sequences might be more or less effective for learning. First, theories of conceptual change have long emphasized that an important first step in learning is generating conflict with current conceptions (Limón, 2001; Posner, Strike, Hewson, & Gertzog, 1982). This *cognitive conflict* approach is based on the theory that learners must first become dissatisfied with their previous conceptions when learning a new concept. Accordingly, this suggests the conflict produced in the implicit training condition in Experiment 1 should occur *before* direct instruction. While the evidence that inducing conflict prior to instruction on science concepts is mixed (Chinn & Brewer, 1993; Lee & Byun, 2012), this is a common pedagogical technique in science education. As such, there are valid instructional reasons to examine if the sequence consistent with the *cognitive conflict* strategy improves learning.

Second, sequencing implicit training tasks *before* direct instruction may enhance explicit conceptual learning by providing “a time for telling” (Schwartz & Bransford, 1998). Opportunities to analyze a range of examples related to a concept can help people become sensitive to information in learning materials that they might otherwise overlook. Encountering examples of sinking and floating objects that are incongruent with intuitive rules might prepare participants understand an explanation from direct instruction materials. The prediction, then, is that when implicit learning is engaged before direct instruction about a scientific concept, people are more likely to later recall and apply this information.

Third, recent developments in conceptual change research suggest that cognitive conflict is more effective when sequenced *after* direct instruction on science concepts (Potvin, Sauriol, & Riopel, 2015). According to the *prevalence model* (Potvin, 2013), conceptual change occurs in three stages: (1) making scientific concepts available; (2) installing inhibitive “stop signs” for intuitive ideas (i.e., cognitive conflict); and (3), increasing the automaticity of the application scientific concepts to various examples. The first stage of this model relies on gaining explicit knowledge of science concepts. As shown in Experiment 1, scientific concepts are not likely to be discovered through implicit training, so direct instruction is likely to be more effective for this stage. The implicit training task from Experiment 1 may be helpful for addressing the latter two stages in the *prevalence model*. Inhibitive “stop signs” can be installed by making predictions and getting feedback about sinking and floating objects that are incongruent with intuitions. The implicit training task also provides opportunities to develop fluency in applying scientific concepts across multiple situations, addressing the third stage of the *prevalence model*.

To test the effects of combining instructional tasks in different sequences, participants in Experiment 2 engaged the implicit training task from Experiment 1 either *before* or *after* watching a direct instruction video on concepts relevant to sinking and floating. In addition to the *direct* + *implicit* and *implicit* + *direct* conditions, a *direct instruction* only condition was tested for comparison. The effect of these instructional tasks was measured in terms of both the implicit, intuitive knowledge and explicit conceptual knowledge gained during the tasks. The instruments used were the same as those in Experiment 1. Namely, implicit intuitive knowledge was measured by performance on sinking and floating predictions (accuracy and reaction time), and explicit conceptual knowledge was measured by answers to selected-response items and reasoning prompts.

Research Questions and Hypotheses

Experiment 2 addresses two research questions:

RQ 2-1. *Does the combination of implicit and direct instruction tasks have an increased effect on learning?*

We hypothesize that combining implicit training with direct instruction will result in increases in both intuitive and conceptual knowledge. Research on implicit learning suggests that although implicit and explicit knowledge are distinct (Batterink, Reber, Neville, & Paller, 2015; Berry & Broadbent, 1988; Green & Flowers, 2003), they can influence one another when learning tasks combine these forms of knowledge (e.g., Mathews, et al. 1989; Reber, et al., 1980; Rünger & Frensch, 2008; Sun, Mathews, & Lane, 2007). We predict that participants in conditions that combine implicit and direct instructional tasks will gain more implicit and explicit knowledge of sinking and floating objects than these types of training presented alone. Alternatively, if these types of training tasks do not help facilitate learning from one another, the learning effects will be similar across all conditions.

RQ 2-2. *How does the sequencing of implicit training and direct instruction influence the knowledge gained from these tasks?*

Two competing hypotheses suggest different learning outcomes with regard to sequencing. According to the *conceptual conflict model* (Limón, 2001; Posner, Strike, Hewson, & Gertzog, 1982) participants in the *implicit* + *direct* condition are predicted to have a learning advantage because cognitive conflict provides motivation for subsequent learning. That is, the conflict that arises from the *implicit training* increases the likelihood that they will learn from the *direct* instructional materials. On the other hand, the *prevalence model* (Potvin, 2013) predicts that participants in the *direct* + *implicit* training condition will demonstrate superior learning because the science concepts are made available through direct instruction prior to application to examples in the implicit learning task. This affords learners the opportunity to develop fluency with concepts, making it more likely that they can express these ideas later.

Methods

Design

This study employed a between-subjects design in which the main factor was training condition with 3 levels –*direct instruction, implicit* + *direct,* and *direct* + *implicit*. The response variables were accuracy and reaction time performance on the sinking and floating prediction task, which had two within-subjects factors with two levels (congruent/incongruent and new/old) and conceptual knowledge assessments. Individual differences were assessed using two well-established EF measures (DCCS and Flanker tasks).

Participants

Based on the sample size analysis and results of Experiment 1, thirty-nine participants were recruited from the University of Minnesota via class announcements and recruitment postings. Participants ranged in age from 18-34 (*M* = 20.8, *SD* = 3.47) years old and 29 were female. Participants were tested individually in a lab room during sessions that lasted approximately 55 minutes and were compensated with course credit or a $10 gift card.

Materials

The materials for Experiment 2 were identical to those used in Experiment 1, with the addition of a *direct instruction* training module. This consisted of a 5.5-minute long video designed to provide teachers with background knowledge related to a middle school science unit on density. This video was adapted from content on the American Chemical Society's "Middle School Science" website (www.middleschoolscience.com) and covered topics such as the calculation of density, the density of water, the molecular structure of wax and clay, and how density relates to sinking and floating objects (the full content of the video is described in Appendix D). Participants were given a brief introduction to the video and told to pay close attention throughout the video, with the goal of trying to learn as much as possible.

Procedure

Participants were randomly assigned to 1 of 3 conditions: *direct, implicit* + *direct,* and *direct* + *implicit.* Each session began with a free response prompt (the same used in Experiment 1) asking participants to describe their knowledge of rules governing sinking and floating objects. This was followed by the DCCS task in all conditions to provide a measure of inhibition ability. In the *direct instruction* condition, participants watched the video only. In the *implicit* + *direct* condition, participants were first given the *implicit training* task described in Experiment 1, followed by the video from the *direct instruction* condition. In the *direct* + *implicit* condition, the video followed the *implicit training* task.

After the training phase, all participants completed the Flanker task as a second measure inhibition ability. This was followed by the sinking and floating prediction task to measure intuitive knowledge about sinking and floating. Finally, each participant completed the same conceptual knowledge measures—the conceptual test, agreement with intuitive rules, and free response prompt (identical to pre-training task)—as participants in Experiment 1.

Results

Training task performance. In two of the three conditions, participants engaged in an implicit training task. Training task accuracy and reaction time performance was analyzed to determine if sequencing the task before or after direct instruction had an effect on performance during training.

Training accuracy on the implicit training tasks was analyzed using a 2 x 2 mixed model ANCOVA, with Training condition (*implicit* + *direct* and *direct* +

implicit) as a between-subjects factor with two levels and trial Congruence (congruent / incongruent) as a within-subjects. Inhibition ability was included as a covariate in the model to control for individual differences. Analysis revealed a main effect of Congruence (F (1, 24) = 28.596, $p < .001$, $\eta^2 = 0.267$), with accuracy on congruent trials (M = .95, SE = .01) significantly higher than on incongruent trials (M = .85, SE = .01). The accuracy results for the implicit training task across the two conditions are shown in Figure 5.1 (top).

This result provides evidence that participants employed prior intuitive knowledge when making predictions during the training task. Participants relied on prior intuitive knowledge, regardless of whether the implicit learning task occurred before or after direct instruction.

To further determine whether there were differences in training performance in different sequences, reaction time data was compared. Prior to analyzing reaction time data, RTs were trimmed and transformed following guidelines outlined by Whelan (2008). To minimize effects of outliers, large RTs were truncated to 8000 ms, approximately 3 standard deviations above the mean. This resulted in 1.5% of observations being truncated. To maintain power, RTs were subjected to log transformation prior to analysis.

A 2 x 2 mixed ANCOVA (Condition by Congruence) was performed on the truncated and log-transformed data, with inhibition ability score as a covariate. This analysis showed a main effect of Congruence (F (1, 24) = 31.655, $p < .001$, η^2 = 0.088). Across *direct* + *implicit* and *implicit* + *direct* conditions, participants were slower to respond on congruent trials (Median RT = 1376.5 ms, SE median = 120 ms) than incongruent trials (Median RT = 1106.5 ms, SE median = 67 ms). Reaction time data is summarized in Figure 5.1 (bottom).

The results of the analysis of reaction time data further support the claim that participants use prior intuitive knowledge to make sinking and floating predictions during training. Faster responses on incongruent trials indicate that participants relied on intuitive rules to make their predictions.

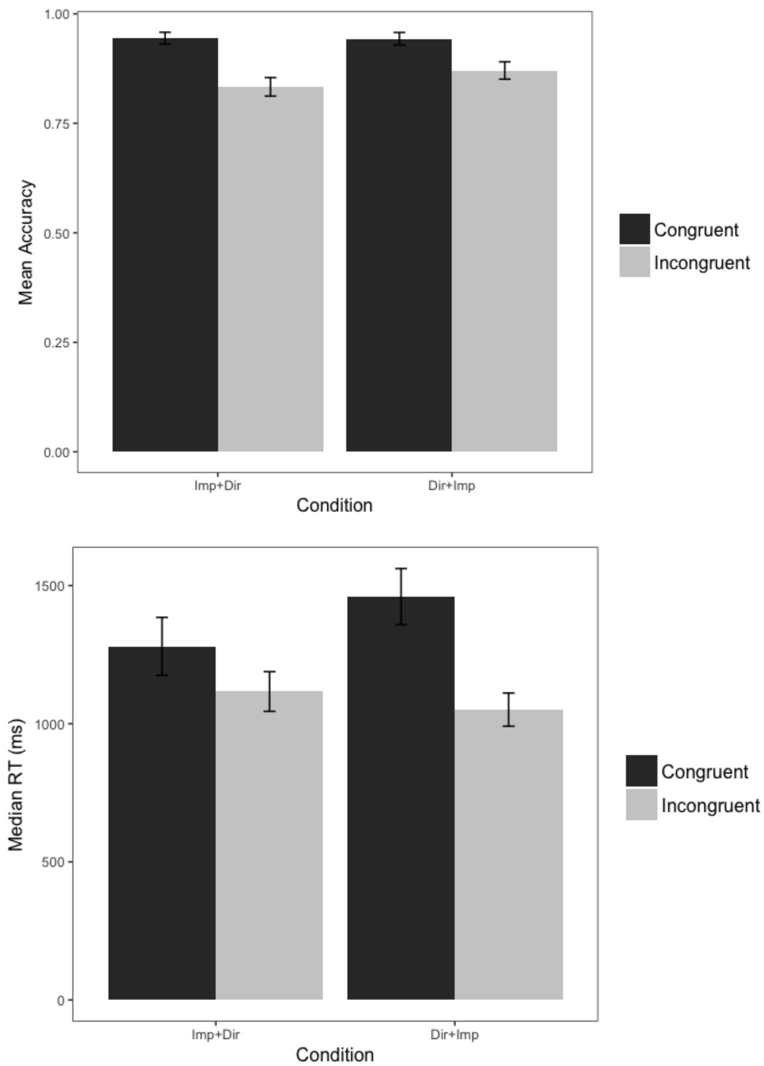


Figure 5.1. Training task performance for Experiment 2. Accuracy (top) and median RT (ms) (bottom) for each group and each level of congruence.

Sinking and floating prediction task performance. To examine the effect of combining implicit training tasks with direct instruction on intuitive knowledge, sinking and floating prediction accuracy data was analyzed using a 3 x 2 x 2 mixed ANOVA, with a between-subjects factor with 3 levels (Training: *direct, implicit + direct,* and *direct + implicit*) and 2 within-subjects factors with 2 levels each

(Congruence*: congruent* and *incongruent;* Novelty*: old* and *new*). Inhibition ability scores were included as a covariate in the model to control for individual differences. This analysis revealed a significant main effect of Congruence, $F(1, 36) = 20.411$, $p < .001$, $\eta^2 = 0.124$ where congruent trials ($M = .93$, $SE = .01$) were significantly more accurate than incongruent trials ($M = .83$ $SE = .01$) ($p < .001$). The results displayed in Figure 5.2 show that the effect of Congruence was smaller in the *direct + implicit* condition compared to other conditions. This pattern was more pronounced in *new* trials. However, this interaction effect failed to reach significance ($F(2, 36) = 3.244$, $p = .0506$, $\eta^2 = 0.012$). The effect of Congruence suggests that participants across all groups were more likely to make accurate predictions when objects had features that were congruent with intuitive rules about sinking and floating.

Prior to analyzing reaction time data, RTs were trimmed and transformed following guidelines outlined by Whelan (2008). To minimize effects of outliers, large RTs were truncated to 8000 ms, approximately 3 standard deviations above the mean. This resulted in 1.1% of observations being truncated. To maintain power and better meet the normality assumptions of the statistical model employed, RTs were subjected to log transformation prior to analysis.

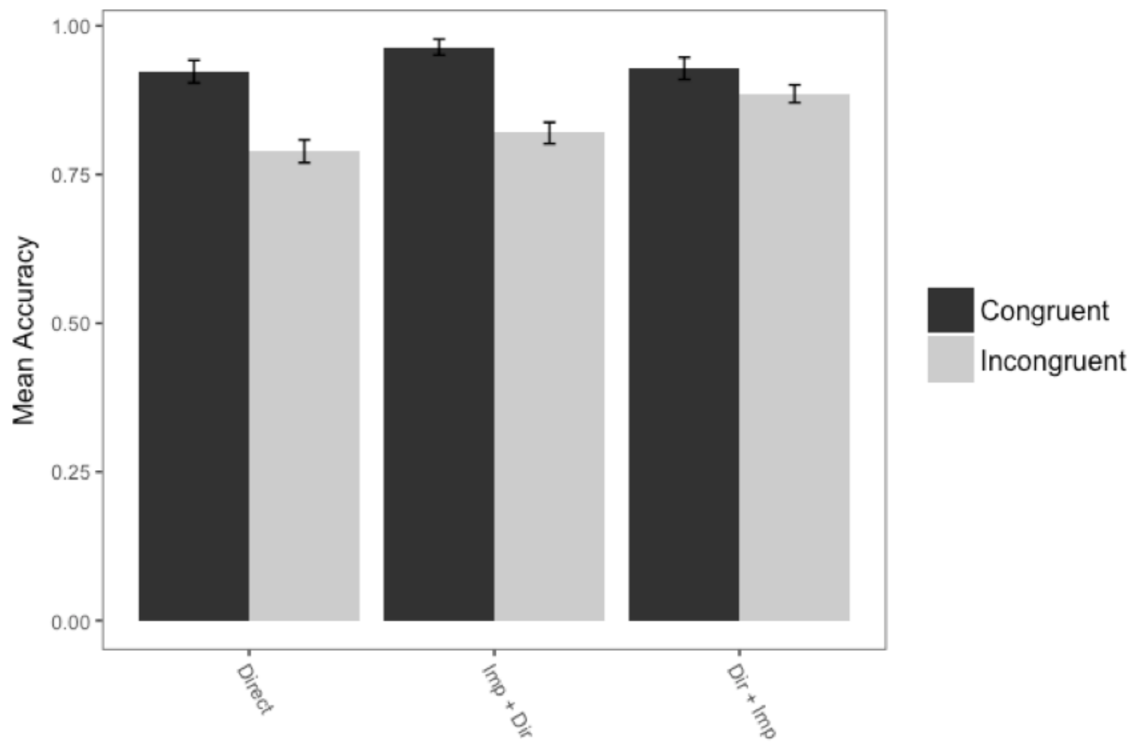


Figure 5.2. Accuracy on sinking and floating prediction task in Experiment 2.

Sinking and floating prediction RT data were analyzed using a 3 x 2 x 2 mixed ANCOVA, with a between-subjects factor with three levels (Training: *direct, implicit* + *direct,* and *direct* + *implicit*), two within-subjects factors with two levels each (Congruence: congruent and incongruent; Novelty: old and new), and inhibition ability score as a covariate. This analysis revealed main effects of Training (F(2, 36) = 6.147, p =.005, η^2 = 0.233) and Novelty (F(1, 36) = 12.251, p =.001, η^2 = 0.011). These main effects were qualified by a significant two-way interaction of Training by Congruence (F(2, 36) = 3.496, p =.027, η^2 = 0.013). Further examination of this interaction showed that the pattern of the effect of Training on RT was different for congruent trials and incongruent trials. For congruent trials, RTs showed the following pattern: *direct* > *implicit* + *direct* > *direct*

+ *implicit* (*p*s < .035). For incongruent trials, the following pattern was observed: *direct* = *implicit* + *direct* > *direct* + *implicit* (see in Figure 5.3). RTs for incongruent trials in the *direct* and *implicit* + *direct* were not significantly different (p = .450), but both were significantly longer than incongruent trials in the *direct* + *implicit* condition (*p*s < .001). The effect of combining implicit training with direct instruction was that it resulted in faster responses, but only on trials that were congruent with intuitive rules. For incongruent trials, faster responses only occurred when direct instruction came before the implicit training tasks. This supports the prediction made by the *prevalence model* that the providing scientific concepts before application to examples is more effective in developing scientific understanding.

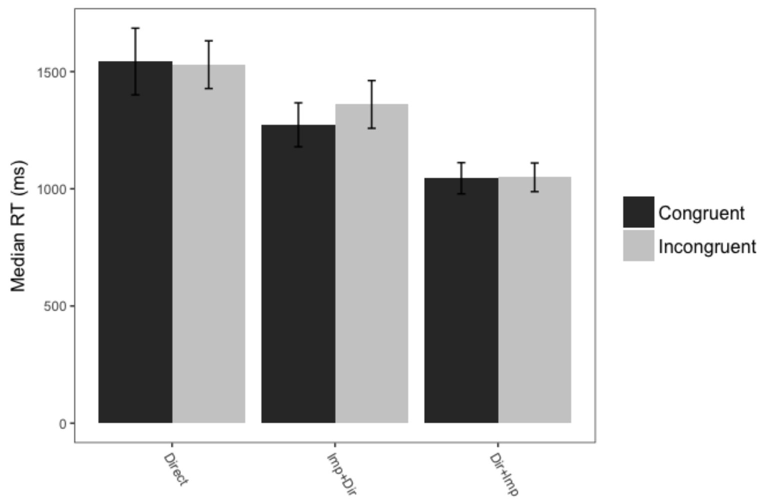


Figure 5.3. Reaction times on sinking and floating prediction task for Experiment 2.

Conceptual test measure. The effect of combinations of implicit learning tasks and direct instruction on conceptual knowledge was measured using a test of conceptual knowledge following training. Written responses were rated according to a rubric (see Appendix B) by the researcher and an additional rater blind to experimental conditions. Ratings were made by the researcher and an additional rater blind to experimental conditions. There was an acceptable level of agreement between raters (Cohen's kappa = .698 across all items) and disagreements were resolved through discussion. The test of conceptual knowledge had high reliability (Cronbach's α = .88). The mean total score was 21.90 out of a maximum of 32, with a range of 5.5 to 32, and *SD* = 7.75. Selected and written reasoning responses for each condition, as well as the total summed score, showed no significant differences among groups based on analysis employing two-way ANCOVAs, with Training as a between-subjects variable and inhibition ability score as a covariate (*p*s > .74).

Table 5.1.

Summary of Conceptual Test Measures for Experiment 1

	Training Condition				
	Direct *n= 13*	Implicit+Direct *n= 13*	Direct+Implicit *n= 13*		
	Mean (SE)	*Mean (SE)*	*Mean (SE)*	*F*(2,36)	*p*
Selected Response	8.4 (0.7)	8.8 (0.8)	8.4 (0.8)	0.298	0.744
Written Reasoning Prompts	13.5 (1.3)	13.1 (1.7)	13.5 (1.6)	0.011	0.989
Total	21.9 (1.8)	21.9 (2.5)	21.9 (2.3)	0.069	0.934

A summary of the results of the conceptual knowledge test for each *training* condition is given in Table 5.1. These results suggest that combining implicit training tasks with direction instruction did not provide a significant advantage in terms of explicit knowledge related to sinking and floating. However, this claim should be interpreted with caution due to the small sample size in this experiment.

Pre-post density knowledge assessment. Responses to the pre-post free-response knowledge prompt (same from Experiment 1) were coded from 0 to 5 points by the researcher and an additional rater blind to experimental conditions. There was a satisfactory level of agreement between raters (Cohen's kappa = .701, p < .001 across all ratings) and disagreements were resolved through discussion. Based on a non-parametric analysis of variance (Kruskal-Wallis test), pre-training response scores were statistically equal across Training conditions ($H(2) = 0.175$, $p = .916$). A Wilcoxon Signed-Ranks Test indicated that post-training scores were significantly higher than pre-training scores, $Z = 322.5$, $p < .001$. Non-parametric analysis of variance (Kruskall-Wallis test) showed that there was no significant effect of Training condition on gain scores ($H(2) = 0.079$, $p = .962$). Table 5.2 provides a summary of the pre-post density knowledge results. These results provide further evidence that combining implicit training tasks with direction instruction did not provide a significant advantage in terms of explicit knowledge related to sinking and floating. This may have been due to the fact that the direct instruction improved explicit knowledge and reasoning equally across all conditions.

Table 5.2.

Pre-Post Explicit Knowledge Assessment Results for Experiment 2

	Training Condition				
	Direct *n= 13*	Implicit+Direct *n= 13*	Direct+Implicit *n= 13*		
	Mean (SE)	*Mean (SE)*	*Mean (SE)*	*H*(2)	*p*
Pre	2.30 (0.38)	2.15 (0.37)	2.08 (0.26)	0.175	.916
Post	3.15 (0.25)	2.85 (0.25)	3.00 (0.20)	1.235	.539
Pre-Post Gain	0.85 (0.32)	0.69 (0.40)	0.92 (0.18)	0.547	.761

Agreement with intuitive rules. Participants' agreement ratings for statements reflecting intuitive rules regarding sinking and floating objects is summarized in Table 5.5. There were no statistical differences in agreement ratings among Training conditions for all but one of the intuitive statements. Participants in the *Direct* condition had ratings indicating stronger agreement with the intuitive statement "Objects made of wood always float," than participants in the *Implicit + Direct* condition ($Z = 21$, $p = .013$). This result shows that combining implicit and direct training may have a negative effect on explicit knowledge about accurate intuitive rules. In this case, participants in the *direct* condition were more likely to agree with an accurate intuitive rule. This result appears to be contradictory with implicit knowledge demonstrated by these groups, as participants in each of these groups demonstrated similar performance on congruent trials during the sinking and floating prediction task.

Table 5.3.

Mean Agreement Ratings with Intuitive Rules for Experiment 2

	Training Condition				
	Direct	Implicit+Direct	Direct+Implicit	$H(2)$	p
Inaccurate intuitive statements					
"Objects with holes always sink"	3.92 (0.34)	4.25 (0.49)	4.20 (0.36)	0.57	.75
"Hollow objects always float"	3.83 (0.42)	3.50 (0.50)	4.10 (0.35)	0.29	.86
"Heavy objects always sink"	4.58 (0.34)	3.37 (0.56)	4.40 (0.40)	2.58	.27
"Light objects always float"	4.25 (0.35)	3.63 (0.68)	4.10 (0.46)	0.54	.76
"Large objects always sink"	4.50 (0.34)	4.50 (0.38)	4.70 (0.15)	0.02	.99
"Small objects always float"	4.91 (0.08)	4.50 (0.38)	4.90 (0.10)	3.11	.21
"Objects made of iron always sink"	3.08 (0.58)	2.75 (0.62)	2.70 (0.58)	0.05	.97
"Objects made of clay always sink"	4.58 (0.26)	4.00 (0.38)	3.60 (0.52)	1.83	.40
Accurate intuitive statements					
"Objects made of wood always float"	2.58 (0.45)*	3.75 (0.52)*	3.00 (0.58)	6.73	.03*
"Objects made of wax always float"	2.67 (0.59)	3.75 (0.45)	3.40 (0.50)	1.97	.37

Ratings are coded with ‘1’ as ‘agree’ and ‘5’ as ‘disagree.’ Non-parametric statistical tests (Kruskal-Wallis and Wilcoxon) were used to analyze differences across conditions. Statistically significant differences are noted with a * $p < .05$).

Relationship between performance on prediction task and conceptual assessment. To examine the relationship between different types of knowledge, the correlations between prediction accuracy and conceptual test scores were calculated for each Training condition. For this analysis, data from all participants were included. Rank-ordered correlations were calculated (Kendall's τ) to avoid violating assumptions of normality. The correlations between performance on sinking and floating predictions and the conceptual test for the *direct* and *implicit + direct* Training conditions were strong, positive, and significant (ps < .04). For participants in these conditions, higher prediction accuracy on the sinking and floating prediction task was associated with higher scores on the conceptual knowledge assessment. The correlation for the *direct + implicit* condition was not significant ($p = .312$). That is, there was no association between the two types of scores in the *direct + training* condition. The correlation and significance statistics are presented in Table 5.4 and the data is summarized graphically in Figure 5.4.

Table 5.4.

Kendall's Rank Correlations between Conceptual Test Scores and Sinking and Floating Prediction Task Accuracy for Experiment 2

Training Condition	τ	*p*
Direct	.54	.013*
Implicit + Direct	.46	.031*
Direct + Implicit	.22	.312

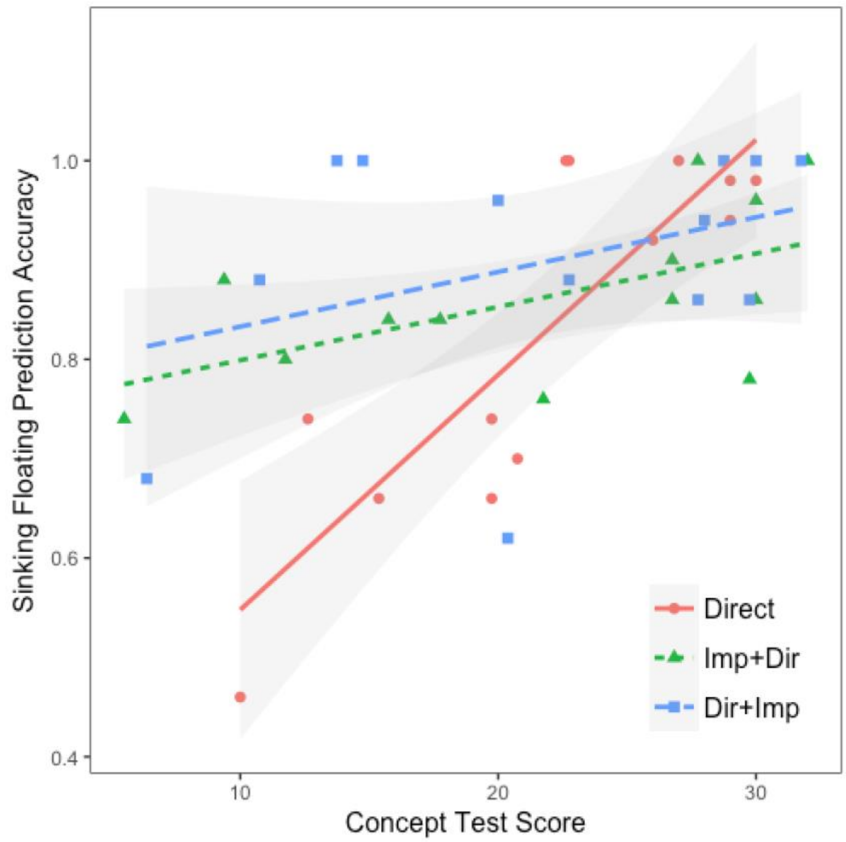


Figure 5.4. Relationship between conceptual test score and sinking and floating prediction task accuracy by Training condition for Experiment 2.

Discussion

The results of Experiment 2 confirm and extend the findings from Experiment 1. The main finding from Experiment 1 was that tasks designed to engage implicit learning improves performance for predicting sinking and floating objects by reinforcing accurate intuitions and increasing sensitivity to whether or not objects are congruent with prior intuitions. That is, implicit learning tasks can influence intuitive knowledge about sinking and floating. However, Experiment 1 also showed that implicit learning tasks alone are likely not sufficient for developing explicit conceptual knowledge. To encourage development of explicit conceptual knowledge, participants in Experiment 2 were presented with direct instruction on concepts relevant to sinking and floating objects. Experiment 2 explored two research questions: (1) Does combining implicit learning and direct instruction tasks have an effect on the knowledge gained from each? And, (2) does the sequencing of different instructional tasks influence their impact on learning? Below, research questions are considered in terms of implicit intuitive knowledge and explicit conceptual knowledge as measured in the experiment.

Effect of sequences combining implicit learning and direct instruction tasks on implicit intuitive knowledge. The results of Experiment 2 showed that combining implicit learning and direct instruction tasks led to changes in implicit intuitive knowledge, confirming and extending the results of Experiment 1. Performance on the sinking and floating prediction task showed that in general participants in the two conditions that combined training tasks made more accurate and faster responses compared to those that received direction instruction alone. This improvement suggests that combining implicit and explicit learning tasks improves implicit intuitive knowledge.

Gains in accuracy were qualified by a significant three-way interaction of Training by Congruence by Novelty. Analysis of this interaction showed that participants in the *implicit + direct* training condition made accuracy gains on new, congruent trials in comparison to the *direct* training condition (see right side of Figure 5.2). This result for the *implicit* + *direct* training condition is consistent with findings from Experiment 1, which showed that implicit training improved accuracy on congruent trials. This improvement was interpreted as resulting from the reinforcement of correct intuitive rules. This interpretation is further supported by RT data, which showed that these same predictions were faster in the *implicit* + *direct* training condition than in the *direct* condition. Taken together, this provides further evidence that engaging in implicit learning tasks prior to direct instruction provides opportunities to reinforce and consolidate accurate intuitive knowledge.

Accuracy and RTs on new, incongruent trials were not significantly different between these conditions. Given the significant two-way interaction of Training by Congruence on RTs, the observed pattern suggests that participants in the *implicit* + *direct* condition were slower than would have been expected by an effect of Training alone. Consistent with the results of Experiment 1, we interpret this as evidence of cognitive conflict in the *implicit* + *direct* condition. Thus, the overall effect of the sequence combining implicit task training before direct instruction is similar to implicit training alone in terms of how it improves implicit intuitive knowledge—it reinforces correct intuitive rules and slows down incorrect intuitive rules.

Participants in the other combined sequence, the *direct* + *implicit* training condition, made more accurate predictions on new, incongruent trials in comparison to the *direct* condition. Further, the pattern of the RTs for the two-way interaction of Training by Congruence showed that these responses were significantly faster for this condition in comparison to the other conditions. The accuracy and RT for congruent and incongruent trials in the *direct* + *implicit* training condition were similar to one another, suggesting that a similar strategy was applied across these trials. This conclusion is supported by the fact that 8 out of the 11 participants in this condition reported applying the density rule strategy during post-interview. Together, this evidence supports the claim that participants in the *direct* + *implicit* training sequence were more likely to successfully develop and apply a new intuitive rule (i.e. the density rule) when making their sinking and floating predictions.

While both conditions that combined tasks increased explicit knowledge, there is also evidence that direct instruction alone also had significant, yet smaller effects on performance on the sinking and floating prediction task. When compared to *no training* controls from Experiment 1, participants in the *direct* training condition demonstrated faster and more accurate intuitive predictions. These improvements were likely due to conceptual knowledge gains, as 7 of the 13 participants in this condition reported using the density rule strategy at post-interview. This claim is further supported by the lack of evidence of cognitive conflict related to inaccurate intuitive rules (i.e., similar RTs across congruent and incongruent trials).

Effect of sequences combining implicit learning and direct instruction tasks on explicit conceptual knowledge. Analysis of conceptual knowledge measures indicated that the implicit learning task employed in these experiments did not enhance learning from direct instruction. In Experiment 2, no significant effects of training condition were found for the conceptual test scores (including selected-response and reasoning sub-scores), pre-post density knowledge assessment, or for agreement ratings with intuitive statements, with one exception.

The only significant effect found in Experiment 2 conceptual knowledge measures was for agreement ratings for the statement "Objects made of wood always float" showed a significant effect of Training, with participants in the *direct* training condition agreeing more with this statement than participants in the *implicit* + *direct*. This result is incongruent with performance on trials with objects made of wood; participants in the *implicit* + *direct* condition made predictions that were more accurate (M = .98) and faster (*Median* RT = 1053 ms) than those made by participants in the *direct* condition (M = .79, *Median* RT = 1588.5 ms). This suggests that performance on these trials was not informed by explicit knowledge of a rule that “Objects made of wood always float.” One possible explanation for these observations is that the implicit knowledge leveraged for performance on sinking and floating predictions does not correspond with agreement ratings of explicit statements of intuitive rules. That is, explicit and implicit knowledge did not correspond.

Although there was a lack of effect of condition within Experiment 2, comparisons across Experiment 1 and 2 training conditions (i.e., ignoring the *no training* condition) showed significant differences in two conceptual test measures across experiments. First, participants in Experiment 2 were more likely to report using the density rule strategy at post-interview (53%) vs. participants in Experiment 1 (19%) (t (58) = -3.01, p = .004). Second, Experiment 2 showed greater gains in pre-post density knowledge response ratings (Experiment 1 = 0.306 vs. Experiment 2 = 0.937, t (62) = -2.63, p = .011). These differences provide evidence that direct instruction employed across Experiment 2 conditions improved explicit conceptual knowledge related to sinking and floating.

There are theoretical reasons to support the finding that combining implicit training with direct instruction did not lead to improvements in explicit knowledge. First, gaining conceptual knowledge of sinking and floating involves representations of concepts independent from implicit knowledge. Thus, a lack of a “bridge” between implicit and explicit knowledge may account for the lack of a synergistic effect. It has been previously suggested that “analogical bridges” (Clement, 1993) or meta-representational processes (Karmiloff-Smith, 1986) may be important for making implicit knowledge accessible to conscious thought. Second, the information contained in implicit knowledge may not be sufficient to support scientific explanation. While people are able to implicitly learn to improve their performance in contexts governed by complex sequence and interactions, these improvements are based on covariation rather than causal relationships (e.g. Lewicki, 1986). Thus, implicit learning may be limited in its ability to support universal scientific principles.

Relationship between implicit intuitive knowledge and explicit conceptual knowledge. The findings from Experiment 2 build on the claim from Experiment 1 that intuitive knowledge and conceptual knowledge develop independently. Research on implicit learning shows that performance on implicit learning tasks can improve based on implicit knowledge that develops independently from explicit knowledge; this implicit knowledge is unconscious and unavailable for verbal report (Batterink, et al., 2015; Berry & Broadbent, 1984, 1988; Hayes & Broadbent, 1988; Reber, et al., 1980). Some researchers suggest that the independence of implicit and explicit knowledge may be due to separate memory systems for each type of learning process (e.g., Amsel, et al., 2008; Reber & Squire, 1994; Willingham, 1998); others argue that a single system is responsible for both types of knowledge (e.g. Shanks & St. John, 1994;

Although these implicit and explicit learning processes may occur separately, researchers propose that implicit knowledge can become explicit under certain circumstances, such as unexpected events (Frensch, et al., 2003; Rünger & Frensch, 2008), re-representation in metamemory (Dienes & Perner, 1999; Karmiloff-Smith, 1986), and sequencing of implicit and explicit learning tasks or hints (Berry & Broadbent, 1988; Mathews, et al., 1989; Sun, Mathews, & Lane, 2007). Common to these accounts is the view that knowledge develops from implicit to explicit. The results of the *implicit + direct* condition in Experiment 2 did not provide evidence for a synergistic effect of these types of learning in this direction. There are several reasons this might have occurred. One possibility is that the implicit learning task did not induce sufficient meaningful conflict (Chan, Burtis, & Bereiter, 1997; Limón, 2001) to engage hypothesis testing associated with explicit learning (Rünger & Frensch, 2008). For example, short stimulus presentation times can reduce explicit learning, even under intentional task instructions (Arciuli, Torkildsen, Stevens, & Simpson, 2014). Another possibility is that the conceptual knowledge required for success on the assessments used was not sufficiently addressed by the implicit learning task. That is, the knowledge generated from the implicit learning task did not adequately match the material covered in the direct instruction to improve explicit conceptual knowledge.

On the other hand, Experiment 2 provides evidence that explicit knowledge gained from the direct instruction could improve performance on the implicit knowledge assessment. The majority of participants in the *direct* and *direct + implicit* training conditions (6 of 10 and 8 of 11, respectively) reported using the density rule strategy to make sinking and floating predictions. Although these participants had explicit knowledge of the density rule, the application of the rule was not reliably translated to intuitive judgment performance (4 of these 14 participants were accurate < 90% of the time). These findings suggest that combining direct instruction with implicit science tasks may improve learning, however, effective transfer may require more opportunities for making connections.

Implications for conceptual change theory. Experiment 2 provides some evidence to support the *prevalence model* of conceptual change (Potvin, 2013). This model predicts that conceptual change occurs when opportunities for conceptual conflict occur after scientific concepts have been made available. The results of the *direct + implicit* training condition showed that learning the density strategy rule could improve performance on the sinking and floating prediction task. In particular, responses on new, incongruent trials were faster and more accurate in comparison to the other training conditions in Experiment 2. The pattern of responses for participants in this condition suggests that they made judgments based on the density rule. That is, they had the opportunity to develop fluency applying a new, scientifically accurate rule.

A key component of the *prevalence model,* as well as other models of knowledge revision, is the idea of *co-activation.* Co-activation of prior inaccurate knowledge and newly-acquired accurate knowledge has been proposed as a key process in knowledge revision (Kendeou & O’Brien, 2014; Ohlsson, 2009) because it allows for competition between intuitive and conceptual knowledge. *Response* *competition* has been theorized as an important process for resolving differences between prior and new conceptions (Ramsburg & Ohlsson, 2016). In the case of sinking and floating, introducing direct instruction prior to the implicit learning tasks could enhance learning for conceptual change by co-activating intuitive rules knowledge during implicit learning tasks. Unlike the *direct* and *implicit + direct* conditions, the *implicit + direct* training affords the opportunity to co-activate both incorrect scientific intuitions and correct scientific concepts during the implicit learning task. Thus, the *implicit + direct* training sequence may provide an important opportunity for revising intuitive knowledge about sinking and floating objects by putting inaccurate intuitive rules and the density rule in competition with one another. This condition did not produce appreciable gains in explicit conceptual knowledge over and above the gains provided by direct instruction, so further research is needed to determine if this sequence of learning can be leveraged to enhance conceptual knowledge gained through explicit learning.

Previous studies have suggested that the superiority of *prevalence model* to the *cognitive conflict model* for conceptual change (Potvin, Sauriol, & Riopel, 2015); however, the results of this study do not warrant such an interpretation. Participants in the *implicit + direct* gained fluency with accurate (albeit incomplete) intuitive rules about sinking and floating objects. For example, participants in this condition responded to trials involving objects made out of wood quickly (*Median* = 1053 ms) and at ceiling accuracy levels (98% correct). There was also evidence for cognitive conflict in the slowed responses to incongruent items. Further research is needed to determine how and if this subtle form of conflict can be utilized to build conceptual knowledge.

Chapter 6: General Discussion

This dissertation proposes that implicit learning is both a source of, and influence on, intuitive scientific knowledge important for conceptual change. The goal of the research presented is to advance this argument by (a) reviewing and connecting previous research on conceptual change and implicit learning, and (b) demonstrating the application of implicit learning task paradigms to a science concept where students demonstrate strong intuitive knowledge. In addition, the experiments in this dissertation were addressed the following research questions: (1) How do implicit science learning tasks influence scientific knowledge, and (2) How does sequencing combinations of implicit science learning tasks with direct instruction influence scientific knowledge? In answering these questions, I consider two different types of scientific knowledge: implicit intuitive knowledge and explicit conceptual knowledge involved in reasoning.

The results of two experiments provide evidence that implicit learning tasks both activate and suppress intuitive scientific knowledge. Engaging implicit learning in science provides opportunities to activate and reinforce intuitions that provide reliably accurate predictions. Participants in the *implicit* and *incidental training* conditions in Experiment 1 and *implicit + direct* condition in Experiment 2 showed increased accuracy and shorter reaction times on trials where intuitive rules and scientific concepts were congruent. Developing prior, intuitive knowledge can be a productive source for making accurate predictions, which is consistent with a key principle of constructivist theories of learning (Bransford, Brown, & Cocking, 2000; Cobb, 1994; Smith, diSessa, & Roschelle, 1993).

Implicit learning tasks can also suppress unproductive intuitions by providing opportunities to differentiate between productive and unproductive intuitive rules. This was evident in the “slow down” that occurred on trials where intuitive rules led to inaccurate predictions. Participants that engaged in implicit learning tasks (*implicit* and *incidental* conditions in Experiment 1; *implicit + direct* condition in Experiment 2) demonstrated slower, less accurate predictions on incongruent trials. This observation is interpreted as a subtle, yet important, form of bottom-up cognitive conflict. Implicit learning tasks can disrupt inaccurate scientific intuitions by slowing down intuitive judgements, which could lead to conceptual change. The results of Experiment 1 suggest that further support is needed to capitalize on this change in intuitive knowledge to enhance conceptual learning.

Implicit learning tasks in isolation are unlikely to lead to conceptual change. To develop understanding, a combination of implicit knowledge and direct presentation of scientific concepts may be optimal. Results from Experiment 2 showed that direct instruction improves explicit knowledge and reasoning about a science concept. Combining implicit learning with direct instruction methods presents different potential advantages, depending on the order in which they are presented. On one hand, engaging implicit learning prior to instruction activates productive intuitions that can be coordinated with scientific concepts. It also induces the subtle form of cognitive conflict found in Experiment 1—responses to counterintuitive trials were more inaccurate and slower for participants in the *implicit + direct* condition. As suggested by the *conceptual conflict model* (Nussbaum & Novick, 1982; Posner, et al., 1982), this change in underlying intuitions may represent an important step in the progression toward scientific understanding. On the other hand, introducing direct instruction prior to implicit learning promotes competition between intuitions and science concepts. Results from Experiment 2 showed that participants in the *direct + implicit* condition were faster and more accurate predictions across on counterintuitive trials. Applying newly-acquired scientific concepts during an implicit learning task co-activates this knowledge with prior intuitive ideas. This allows science concepts and conflicting knowledge to compete, thus making it more likely for the science concept to be expressed when intuitions are activated.

The studies described here provide evidence of the effects of implicit learning for scientific intuitions and conceptual knowledge related to sinking and floating objects. However, it is not apparent whether or not these effects (a) can be readily applied to other scientific concepts, and (b) can support conceptual change. In the sections that follow, I review research that provides evidence that activating productive prior intuitions and suppressing unproductive prior intuitions through implicit learning tasks may represent a viable method for supporting and enhancing conceptual change in science and other content areas.

Activating productive intuitions

While the goal of science education is for students to develop accurate, explicit conceptual knowledge of scientific phenomena, it has also become clear that students' prior, intuitive beliefs must also be addressed. Research from a wide range of disciplines, including cognitive science, developmental psychology, and science education, have proposed implicit cognitive elements that influence learning and reasoning about scientific phenomena and often result in misconceptions (Maeyer & Talanquer, 2013). Several of these implicit cognitive elements include: core knowledge (Spelke & Kinzler, 2007), cognitive constraints (Gelman, 2004), fast and frugal heuristics (Gigerenzer & Gaissmaier, 2011), p-prims (diSessa, 1993), ontological categories (Chi, 2008), implicit presuppositions (Vosniadou, 1994; Vosniadou & Skopeliti, 2014), facets of understanding (Hammer & Elby, 2003; Minstrell, 1992, 2001), coordination classes (diSessa & Sherin, 1998), cognitive construals (Coley & Tanner, 2012), and conceptual resources (Redish, 2004; Taber, 2008). Although each of these intuitive elements is associated with different specific features, they each share two common features: (1) they are implicit or tacit forms of knowledge, in that they operate largely outside of conscious recall and control, and (2) they generate and guide productive thinking and reasoning about phenomena.

Viewing students' incomplete, naïve prior knowledge as a productive resource, rather than an obstacle or barrier to mature understanding, is consistent with constructivist views of how people learn (Hammer, 1996; Smith, diSessa, & Roschelle, 1993; Vygotsky, 1978). Constructivist theories assume that knowledge is constructed from previous knowledge, regardless of the form of instruction (Bransford, Brown, & Cocking, 2000; Cobb, 1994; Piaget, 1976; Vygotsky, 1978). Research shows that people use their intuitive knowledge in productive ways to construct explanations of scientific phenomena. For example, children combine their prior knowledge with school-learned knowledge to describe synthetic models of the Earth (Vosniadou & Brewer, 1992); biology undergraduate majors use teleological assumptions when reasoning about evolutionary phenomena (Coley & Tanner, 2015); undergraduate chemistry students rely on “intuitive, spurious, and valid assumptions about the nature of chemical entities” when reasoning about structure-property relationships in the context of chemical reactions (Maeyer & Talanquer, 2013). While reasoning from intuitions can lead to scientifically inaccurate conclusions and expressions, shifting among these intermediate conceptions may represent an important progression in the development of scientific knowledge (Sadler, 1998). Further, these intuitions can provide valuable resources for instruction (e.g. Hammer 1996).

Given that productive intuitions represent both knowledge-in-transition and resources for future learning, how can implicit science learning tasks help build and activate these intuitions? The experiments presented in this dissertation show that productive intuitions about sinking and floating can be reinforced through implicit learning tasks. Studies exploring implicit learning applied in two other domains, electricity and food nutrition, demonstrate the viability of these types of tasks across scientific concepts.

Researchers have developed methods to study how people develop scientific intuitions about electricity concepts by employing learning tasks similar to implicit learning paradigms. A study by Chasseigne, Giraudeau, Lafon, & Mullet (2011) was designed to examine improvements in students’ ability to induce intuitions about electrical resistance in simple circuits. In each trial of the task, labeled diagrams of electrical circuits were presented to 7th grade, 9th grade, and college students, and their task was to mark an “X” on a scale to indicate the degree of electrical resistance. During learning sessions, participants were presented with feedback on their judgments. The overall procedure involved 3 test sessions of 18 trials each and 2 learning sessions (35 trials, conducted in between first and second test sessions). The results showed that 25% of students were able to develop accurate intuitive knowledge of the inverse relationship between electrical current and voltage to make predictions about resistance. A larger proportion were able to accurately associate the relationship between one variable and the output. Most students were able to learn the direct relationship between electrical resistance and voltage (55%), and about one-third (32%) of students learned the inverse relationship between resistance and current.

The results of this experiment further support the claim that implicit learning leads to the reinforcement of accurate scientific intuitions (i.e. positive relationship between voltage and resistance) in the absence of formal symbolic representations of this knowledge. Similar to the density concept involved in sinking and floating, the concept of electrical resistance involves a ratio between two quantities: voltage and current. Although more participants in this study were able to intuit the relationships involved in electrical resistance compared to what was found in the research presented in this dissertation (about 16% gained the density rule in Experiment 1), this can be explained by the fact that (a) there were more extraneous variables presented in each stimulus, and (b) the electrical concepts presented in this study do not have a high level of prior knowledge associated with them.

Another example of implicit learning in a naturalistic setting is presented in a recent study that examined people's perceptions of organic foods (Perkovic & Orquin, 2017). People have the general belief that organic foods are more nutritious than non-organic foods, despite a lack of conclusive science evidence to support this claim. In a series of studies, Perkovic and Orquin (2017) demonstrated that this belief is grounded in ecological rationality—foods that are organic are more likely to be foods that also happen to be healthy (i.e. you are more likely to find organic apples than organic potato chips). Therefore, people who purchase organic foods are more likely to be purchasing healthful foods. People are not only sensitive to the statistical structure present in the naturalistic environment (Study 1), but can also learn the statistical structure when the correlation of cues (organic and healthy food labels) are manipulated (Study 3). The results of an eye-tracking study showed that people were more likely to fixate on organic labels when they are positively correlated with health cues. This learning occurred despite the absence of explicit instruction about labels or how to use them. This study provides further evidence that people can learn to associate correlating cues that can lead to a productive, yet scientifically inaccurate, intuition (i.e. organic foods = healthful foods). Taken together with the results of the experiments presented here, these results provide evidence that people are able to implicitly learn associations relevant to scientific phenomena, and use these associations when making decisions in situations where conceptual knowledge is absent or has a reduced influence.

Suppressing unproductive intuitions

Although some intuitions can be helpful, others may represent spurious or mistaken associations. For example, while holes may cause some floating objects (such as boats) to sink, an object having holes is not a reliable cue for determining whether an object will sink or float. Thus, in some cases, it may be valuable to suppress, or inhibit, certain associations.

A growing body of research supports the view that experts in science domains suppress, rather than supplant or eradicate, their intuitive knowledge about scientific phenomena. This view is supported by studies that employ measures of reaction time (Shtulman & Varcarcel, 2012; Potvin, Masson, Lafortune & Cyr, 2014) and brain imaging (Dunbar, Fugelsang, & Stein, 2007; Foisy, Potvin, Riopel & Masson, 2015; Masson, Potvin, Riopel, & Foisy, 2014). This implies that somewhere in the learning process, experts learn to suppress their intuitions about scientific phenomena. The question then becomes, *how do people learn to effectively suppress their intuitions?*

One approach for teaching students to suppress inaccurate prior knowledge has been to encourage *cognitive conflict* by presenting explicitly presenting students with anomalous data, disconfirming information, or contradictory situations that violate intuitive rules. Although strategies that directly refute inaccurate beliefs have been successful when those beliefs are relatively isolated (Broughton, Sinatra, & Reynolds, 2007; Guzetti, Snyder, Glass, & Gamas, 1993), the results of implementing cognitive conflict are mixed when addressing conceptual knowledge (see Chapter 3). For example, Tirosh, Stavy, and Cohen (1998) attempted to influence intuitive thinking related to the intuitive rules *'everything comes to an end'* and *'everything can be divided'* in relation to mathematical entities (i.e. quantities) and material (i.e. physical) objects. An instructional intervention presented two statements, one congruent with intuitive rules and one containing a formal rejection, and students were asked to judge the correctness of each statements and give reasons for their judgments. Students' responses to subsequent tasks showed only minor changes to the use of intuitive rules. The researchers conclude that "intuitive rules are stable and resistant to change" (p. 1267).

Other, subtler approaches to cognitive conflict may be fruitful for influencing intuitions. Researchers have examined approaches that activate inhibitory mechanisms prior to intuitive reasoning tasks (Stavy & Babai, 2010). These approaches include solving difficult reasoning problems (Attridge & Inglis, 2015), preactivating inhibitive processes with counterintuitive examples (Babai, Eidelman, & Stavy, 2012), providing warnings about the need to inhibit (Babai, Shalev, & Stavy, 2015), drawing attention to a relevant variable (Dembo, Levin, & Siegler, 1997), incidental experiences of difficulty (Alter, Oppenheimer, Epley, & Eyre, 2007), and taking different perspectives (i.e. self or a logical person's) (Amsel, Klaczynski, Johnston, Bench, Close, & Sadler, 2008; Klaczynski, 2001). These studies show that cognitive conflict strategies that operate by indirectly activating inhibitory mechanisms can result in changes, at least temporarily, in knowledge and reasoning. Changes in intuitive knowledge are observed in behavioral responses to intuitive reasoning tasks in terms of accuracy and reaction times, as well as in brain imaging that shows activations of brain areas associated with inhibitory processes (Stavy & Babai, 2010).

Further, science education researchers have demonstrated the effectiveness of “cognitive perturbation” strategy in improving conceptual knowledge (Dega, Kriek, & Mogese, 2013). This strategy involved asking students to consider multiple, intermediate progressive conceptions related to electricity and magnetism with the aid of a computer simulation. This strategy was compared to a “cognitive conflict” strategy, which involved presenting students with simulation outcomes that conflicted with their previous predictions (i.e. explicit hypothesis testing). Although the conceptual learning gains were relatively small on the whole, students in the “cognitive perturbation” condition made larger gains in conceptual knowledge, as measured by a conceptual inventory assessment. This result gives further support for considering and supporting the importance of smaller, subtler changes in knowledge when attempting to help students achieve conceptual change.

These studies and the experiments described in this dissertation employ relatively short and simple, yet engaging, tasks designed to activate inhibitory processes. The implicit science learning tasks developed for this dissertation accomplished this by presenting a high volume of stimuli that were both congruent and incongruent with intuitions about sinking and floating. Suppression of intuitions was operationalized in Experiments 1 and 2 by the performance patterns observed on incongruent trials on the sinking and floating task. Specifically, a training condition was successful in achieving suppression if responses on incongruent trials were both less accurate and slower than for congruent trials. This was observed in Experiment 1 in the *implicit training* condition and in Experiment 2 in the *implicit + direct training* condition. This “slow down” in relation to inaccurate intuitions is interpreted as a subtle form of cognitive conflict that can promote the suppression of intuitions.

This approach to cognitive conflict addresses the 3 challenges for this strategy outlined by Limón (2001). First, indirect approaches to cognitive conflict create meaningful conflict without relying on student factors such as reasoning ability, prior knowledge, motivation, cognitive engagement, and epistemological beliefs. Instead, they rely on simple, yet engaging, interventions that activate inhibitory processes during tasks that involve intuitive rules. Second, this approach addresses theoretical issues related to conceptual change and the intermediate learning steps related to cognitive conflict. Namely, cognitive conflict happens at the level of implicit, intuitive knowledge rather than explicit, declarative knowledge. Changes that occur at this level are measured in accuracy, reaction time, and brain imaging data that show more inaccurate and slower responses that activate parts of the brain associated with inhibitory processes. Third, these interventions can be implemented with high fidelity without reliance on teacher strategies or training. Given these desirable features, applying implicit learning approaches to conceptual conflict can offer a fruitful strategy to be pursued in future research.

The relationship between intuitive and conceptual scientific knowledge

The division between intuitive and conceptual forms of knowledge and reasoning have long been proposed (e.g. West & Pines, 1984; Amsel et al., 2008). Importantly, “genuine conceptual learning involves the intertwining of these two [forms of knowledge]” (West & Pines, 1984, p. 50). However, until recently, approaches to conceptual change have considered both types from a theoretical perspective. That is, theories of conceptual change have proposed implicit cognitive entities such as p-prims, presuppositions, and ontological categories, in order to explain the existence of explicit forms of inaccurate science knowledge; however, they do little to explain how implicit forms of knowledge can be changed. As a result, the approaches to conceptual change operate largely on explicit, conscious learning and reasoning strategies, such as reading refuting texts (e.g. Broughton, Sinatra, & Reynolds, 2007), encountering anomalous information or discrepant phenomena (e.g. Chinn & Brewer, 1993), or explicit training about empirical and ontological assumptions (e.g. Slotta & Chi, 2006).

Although implicit learning approaches may improve scientific intuitions by activating productive intuitions and suppressing unproductive intuitions, questions remain about how these changes can be effectively leveraged to invoke conceptual change. First, how do learners draw connections between productive intuitions and conceptual knowledge needed for scientific understanding? Second, how does the development of conceptual knowledge influence inhibitory processes? Namely, does conceptual knowledge reduce the need for inhibitory processes, or does the ability to inhibit intuitions improve (Star & Pollack, 2015)? These questions highlight important issues related to the relationship between intuitive and conceptual knowledge. Applying implicit learning methods and theories can provide insights into how the types of knowledge are related.

Much of the research on implicit learning has attempted to define and dissociate it from explicit forms of learning (Cleeremans, Destrebecqz, & Boyer, 1998; Roediger, 1990; Shanks, 2004; Shanks & St. John, 1994); in fact, some models of implicit learning have proposed that the knowledge gained is completely independent from explicit knowledge (e.g. Lewicki, 1986). On the other hand, others suggest that implicit learning can result in explicit, conscious knowledge through the processes of "chunking" (Perruchet & Pacteau, 1990), pattern recognition (Mathews, Buss, Stanley, Blanchard-Fields, & Cho, 1989), or representational redescription (Karmiloff-Smith, 1986). Although the spontaneous development of conscious knowledge is possible, this knowledge is likely to be fragmented and incomplete (Mathews et al., 1989; Perruchet & Pacteau, 1990). Thus, further support is needed to develop complete and accurate conceptual knowledge. For example, having learners make self-explanations about anomalous examples has been shown to increase belief revision when there is a high occurrence of anomalies (Williams, Walker, & Lombrozo, 2012).

Research on implicit learning has implications for the role of prior knowledge in relation to inhibitory processes. Implicit learning can be helped or hindered by prior knowledge, depending the nature of the knowledge. Presenting explicit knowledge about artificial grammar rule structures can enhance implicit learning when presented beforehand by focusing attention on relevant strings (Reber et al., 1980). When an artificial grammar invokes prior knowledge in an incongruent fashion (i.e. expectations are violated), implicit learning is enhanced (Ziori, Pothos, & Dienes, 2014). Thus, prior knowledge can enhance implicit learning by both setting and violating expectations. In both cases, prior knowledge supports implicit learning by focusing learners' attention on relevant features. However, in the case of violated expectations, engaging inhibitory mechanisms may encourage search for relevant associations. This would be consistent with research findings that show that infants spontaneously explore when their expectations are violated (Stahl & Feigenson, 2015) and brain imaging studies that show that activating inhibition can increase logical thinking (Houdé, Zago, Mellet, Moutier, Pineau, Mazoyer, Tzourio-Mazoyer, 2000). This also further demonstrates the separate, yet related, natures of implicit and explicit knowledge.

Implications for other areas of research

The research presented in this dissertation has broader empirical, theoretical, and pragmatic implications for others areas of research, including cognitive psychology, learning science, and science education.

Empirically, this research demonstrates that implicit learning paradigms from cognitive psychology can be applied to a scientific domain important for education. While implicit learning theory has been applied in the area of second language acquisition (e.g. DeKeyser, 2003; Rebuschat & Williams, 2012), implicit learning tasks have not been widely-applied in academic content areas. The research presented here also that extends previous findings from reaction time studies on intuitions in mathematics (e.g., Babai, Zilber, Stavy, & Tirosh, 2010; Stavy & Babai, 2010) and science (Babai & Amsterdamer, 2008; Babai, Sekal, & Stavy, 2009; Potvin et al., 2014; Shtulman & Varcarcel, 2012). The results of this study are consistent with the common finding across reaction-time studies of intuitive ideas: increased reaction times in responses to stimuli that are incongruent with intuitions. While reaction time studies of sinking and floating objects have been previously reported (Potvin et al., 2014), this study extended these findings by presenting single objects (rather than pairs) along with quantitative data, as well as by examining multiple intuitive rules. These methods offer a more fine-grained analysis required to understand transitional knowledge states involved in conceptual change processes (diSessa & Sherin, 1998; Limón, 2001).

The theoretical contributions of this dissertation lie in the connections drawn between theories of conceptual change and implicit learning. This dissertation provides two key insights that bring research from these fields together. First, implicit learning is a source of intuitive prior knowledge students bring to the classroom. Although conceptual change researchers have theorized about implicit conceptual entities, these accounts do not account for how they are acquired. Some researchers, particularly developmental psychologists, have argued that the mental structures underlying intuitive physics and psychology are innate or endowed (e.g. Spelke & Kinzler, 2007; Gelman, 2004); others have challenged this claim of innateness, arguing for an epigenetic view of cognitive development (see Spencer, Blumberg, McMurray, Robinson, Samuelson, & Tomblin, 2009). An alternative view of the development of early intuitive science knowledge is that humans possess a general-purpose implicit learning mechanism that, beginning in early development, is applied to learn from perceptual experiences of the world. These mechanisms enable to people to extract patterns in physical and social phenomena from relatively sparse perceptual input.

A second key theoretical connection is in regard to the nature of intuitive science knowledge and its representation in cognitive systems. As Taber (2008) wrote, “the nature of the scientific concepts themselves, and the contexts in which they are evoked, are likely to be significant factors that interact with features of the individual’s cognitive structure” (p. 1034). Viewing scientific intuitions as products of implicit learning suggests (a) they are qualitatively different from explicit, declarative knowledge, and (b) they are not likely to be changed via explicit knowledge or conflict. This view of the nature of intuitive knowledge has important implications for theories of conceptual change. For example, the second step in the *prevalence model* of conceptual change (Potvin, 2013) involves installing inhibitive “stop signs” for intuitions that lead to misconceptions. Potvin suggests that these “cognitive conflicts should be preferably induced by experimental means, letting nature reinforce (or not) the available conceptions or intuitions. These means should be numerous, rich, and astute in order to prevent any important misleading intuitions from eluding teachers’ efforts” (p. 16). As shown in this dissertation research, implicit learning tasks provide a means for both reinforcing and inhibiting scientific intuitions by engaging in numerous and rich examples, while providing subtle feedback to students without requiring high teacher effort. However, the results of Experiment 2 suggest that providing explicit conceptual information prior to implicit learning tasks (i.e. *direct + implicit* condition) may hinder the installment of inhibitive “stop signs” that were present when implicit learning tasks were presented first.

From a pragmatic standpoint, implementing implicit learning tasks to activate and suppress intuitive thinking in educational settings offers a “less is more” approach to learning science. Given current and ongoing efforts to engage all students in deep knowledge, skills, and cross-cutting themes in science (AAAS, 1993; National Research Council, 2012), there is a high need for instructional methods that reduce, rather than exacerbate, differences in individuals’ abilities, characteristics, and environmental settings. Implicit learning tasks offer several advantages in this regard. First, implicit learning abilities are dissociated from psychometric intelligence, and are more robust and evenly distributed across the population and across age (Gebauer & Mackintosh, 2007; Kaufman et al., 2009). Thus, implicit learning tasks are less dependent on individual abilities to be effective. Second, implicit learning tasks are relatively short interventions that require low effort; therefore, student characteristics such as prior knowledge, motivation and interests, epistemological beliefs, and cognitive engagement are less likely to influence their effectiveness. Finally, because similar scientific intuitions are found across populations of students, tasks developed in one context are likely to be effective for students in another context. Thus, development of implicit learning tasks for various science topics, following the guidelines established in Chapter 3, are likely to be scalable interventions, particularly with the aid of technology.

Limitations and directions for future research

The results of this study show that a relatively brief implicit learning intervention can impact scientific intuitions about sinking and floating objects. This task results in inaccurate, but slower, responses to trials where intuitive predictions are incongruent with scientific ones. While there were significant changes in intuitive knowledge across conditions, the differences in conceptual knowledge scores were not significant. This was likely due to an underpowered sample size for each experiment, as significant differences in conceptual knowledge were found between experiments when samples were pooled (i.e. higher scores in Experiment 2 vs. Experiment 1). This may have also been due to lack of sensitivity and precision in the assessment tasks to differentiate among participants with different levels of conceptual knowledge. Thus, further replication with larger samples and refinement of the conceptual knowledge measures should be pursued in future research.

Another key limitation was due to the sample of participants. The sample across both experiments included a high proportion of females (81%), likely due to the fact that participants were recruited from undergraduate classes in the College of Education (61% female) and College of Design (67% female), which have higher proportions of female students. Thus, while there are no theoretical reasons to expect gender differences in the measures employed in this study, inferences should be tentatively applied to more general populations.

The sample in this study was chosen for convenience and to capture a wide range of prior knowledge. Participants in these experiments were likely to have encountered instruction on the topic of buoyancy / sinking and floating. Although participants in this population showed evidence of employing intuitive rules, these results may not apply to other populations of interest, such as upper elementary or middle school students. Implementation of implicit learning tasks with students at relevant grade levels should be a high priority for future research.

The experiments designed here did not address long-term retention of changes to intuitive knowledge. That is, we do not know whether these changes were retained beyond the 1-hour learning session. Although there is evidence from studies employing similar interventions to suggest that these changes are relatively durable (Chasseigne et al., 2010), further research is needed to demonstrate an extended effect for this task.

A practical extension of this work would be to examine how intuitive reasoning about material in relation to sinking and floating can be leveraged when teaching about density. For example, in the sample of items used in these experiments, implementing a material-based rule strategy would lead to an 89% accuracy rate. Further, a material-based strategy is 100% accurate for objects made of wood and wax, suggesting a productive intuitive rule for making sinking and floating predictions. The question becomes, how can instruction capitalize on this intuitive rule? One possible strategy is employing self-explanations for incongruent examples (Williams, Walker, & Lombrozo, 2012), while another might be providing conceptual explanations for materials at the molecular level (similar to the *implicit + direct* condition). Future studies may be more successful in changing explicit conceptual knowledge by employing additional strategies.

Another area of research that may prove fruitful is in developing models for the response profiles for the sinking and floating prediction task. While we were able to find differences across condition in response patterns by looking at differences in accuracy and response times across congruent and incongruent trials, further analysis of response patterns may provide additional information about the effect of these interventions. Further, computational models of learning may provide additional insight into how implicit learning results in the patterns of responses observed. Two possible candidates for computational models are connectionist / PDP models (McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986) and Bayesian inference models (Gopnik & Bonawitz, 2014; Prefors, Tenenbaum, Griffiths, & Xu, 2011). Each of these models have been successfully applied, respectively, to implicit learning (Cleeremans, Destrebecqz, & Boyer, 1998) and cognitive development (Tenenbaum, Kemp, Griffiths, & Goodman, 2011).

Conclusion

This investigation has proposed and demonstrated how theory and methods from research on implicit learning can be applied to science learning to enhance conceptual change. The experiments presented here show evidence for the activation and suppression of scientific intuitions using tasks that involve making simple judgments about numerous examples. These changes in intuitive knowledge are important for gaining mature scientific understanding associated with conceptual change.

Both researchers and practitioners may find interest in the research presented here. For researchers, grounding theories of conceptual change in cognitive processes can provide insights into unresolved issues regarding the nature of misconceptions and the role of cognitive conflict. Practitioners may gain an appreciation for the complex learning that students are capable of achieving, despite a lack of ability to explicitly state what they have learned. For both, I hope it provides excitement about the possibilities for tapping into learning abilities that have been, up until now, largely ignored.

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Appendix A: Conceptual Test Items

UNIVERSITY OF MINNESOTA
Driven to Discover℠

Directions:

Answer the following questions to the best of your ability.

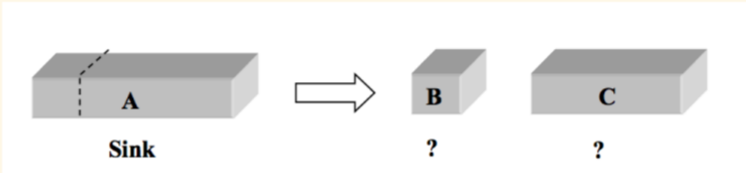
If you need assistance or have any questions regarding the directions, you may ask the experimenter for clarification.

When you are ready, enter your participant ID and click on the ">>" button.

Participant information:

Participant ID

Block A sinks in water. Suppose we cut it into two pieces: Block B is ¼ (one-fourth) of Block A and Block C is ¾ (three-fourths) of the Block A.



When placed in water, Block B will most likely...

- sink
- float
- neither sink nor float

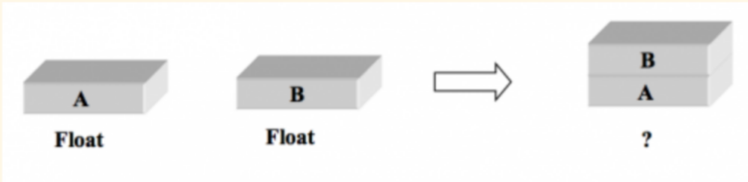
Provide reasoning for your choice:

When placed in water, Block C will most likely...

- sink
- float
- neither sink nor float

Provide reasoning for your choice:

Block A and Block B both float in water. Suppose that we glue them firmly together and place them in water. (Assume the mass of the glue is negligible.)



Together, they will most likely...

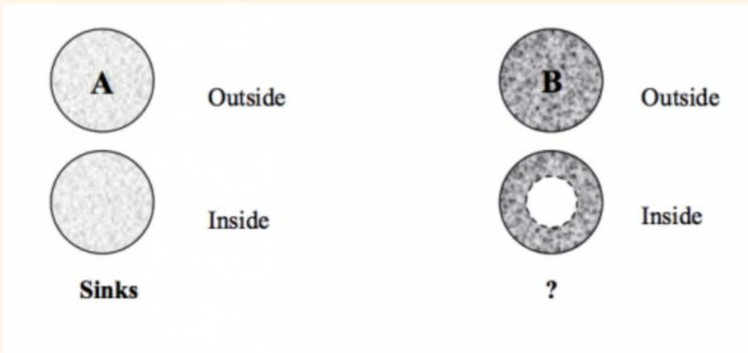
- sink
- float
- neither sink nor float

Provide reasoning for your choice:

Ball A is solid; Ball B is hollow in the center (see the pictures below).

Ball A and Ball B are made of different materials, but they have the SAME mass and the SAME volume.

Ball A sinks in water.



When placed in water, Ball B will most likely...

- ○ sink
- ○ float
- ○ neither sink nor float

Provide reasoning for your choice:

Block C floats on water. Suppose a hole is cut in the block.

When placed in water, Block C will most likely...

- sink
- float
- neither sink nor float

Provide reasoning for your choice:

Block A and B are made of the SAME material. Block B is flatter than Block A. Block A sinks in water.

When placed in water, Block B will most likely...

- sink
- float
- neither sink nor float

Provide reasoning for your choice:

Ball A and Ball B have the SAME mass and the SAME volume.

Ball A is made of soft material. Ball B is made of hard material.

Ball A floats in water.

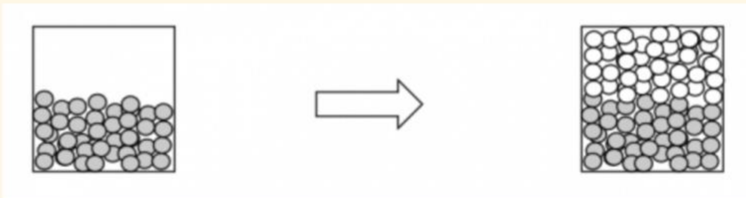
When placed in water, Block B will most likely...

- sink
- float
- neither sink nor float

Provide reasoning for your choice:

A tightly sealed container that is half-filled with rocks sinks in water.

The container is opened and the other half is filled with foam peanuts. The container is sealed tightly again.



SINKS

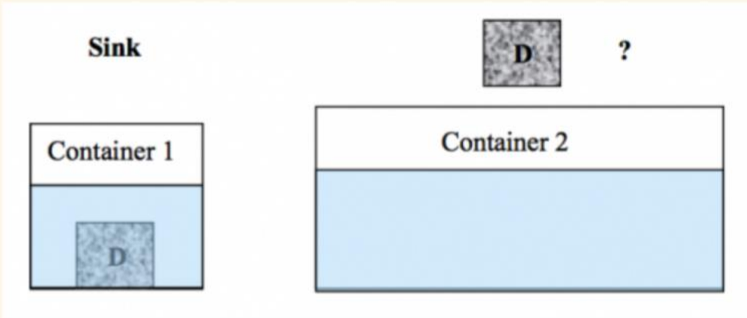
If the container is now placed in water, it will most likely...

- sink
- float
- neither sink nor float

Provide reasoning for your choice:

Block D sinks when placed in water in Container 1.

Block D is placed in Container 2, which is larger and has more water.

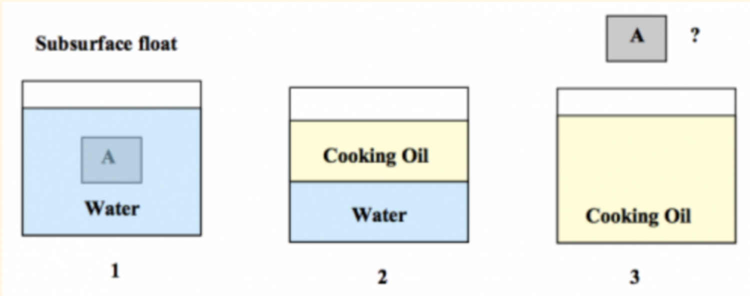


Block D will most likely...

- sink
- float
- neither sink nor float

Provide reasoning for your choice:

Block A neither sinks nor floats in water – it stays below the water surface when placed there (“subsurface float”; see 1). Cooking oil floats on water (see 2).



If Block A is placed in cooking oil (see 3), it will most likely...

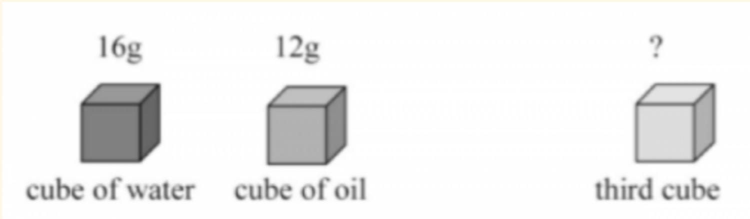
- ○ sink
- ○ float
- ○ neither sink nor float

Provide reasoning for your choice:

The three cubes below are the same size, but they each have a different mass.

The cube of water has a mass of 16 grams.

The cube of oil has a mass of 12 grams.



The third cube floats in water, but sinks in oil.

Which of the following is the possible mass of the third cube?

- ○ 10g
- ○ 11g
- ○ 14g
- ○ 17g
- ○ 18g
- ○ Not possible to determine

The cube of water below has a mass of 16 grams.

Which of the cubes below will likely SINK in water? (Select all that apply)

- [ ] 

- [ ] 

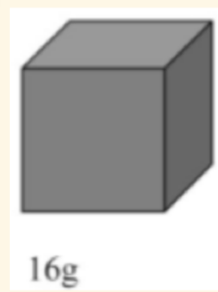
- [ ] 

- [ ] 

- [ ] 

- [ ] 

- [ ] 

- [ ] 

Describe a rule, or set of rules, that can be used to determine whether an object will sink or float in water.

Rate the degree to which you agree or disagree with the following statements.

	Agree	Somewhat Agree	Neither Agree nor Disagree	Somewhat Disagree	Disagree
Objects made of wax always float.	○	○	○	○	○
Heavy objects always sink.	○	○	○	○	○
Objects made of wood always float.	○	○	○	○	○
Objects with holes always sink.	○	○	○	○	○
Objects made of clay always sink.	○	○	○	○	○
Small objects always float.	○	○	○	○	○
Objects made of iron always sink.	○	○	○	○	○
Hollow objects always float.	○	○	○	○	○
Large objects always sink.	○	○	○	○	○
Light objects always float.	○	○	○	○	○

Age

Sex

Are you currently a student?

- Yes
- No

Number of college-level math and science courses taken, including Advanced Placement (AP) courses (approximate, if known):

List college-level math and science courses taken:

Appendix B: Rubric for Reasoning Prompts

Level	Description	Examples
0	Provides no or redundant reasoning; may refer to intuitive ideas as justification	[no reasoning provided]; "Because it will be heavier"; "Hollow things float"
1	Provides either good reasoning with a faulty premise; or correct premise with faulty reasoning	"It doesn't depend on the size of the object but the material." "The volume is the same, but there is more mass."
2	Provides good reasoning and accurate premises and conclusions	"The density of the object is the same as before"

Appendix C: Rubric for Pre-Post Density Knowledge Prompt

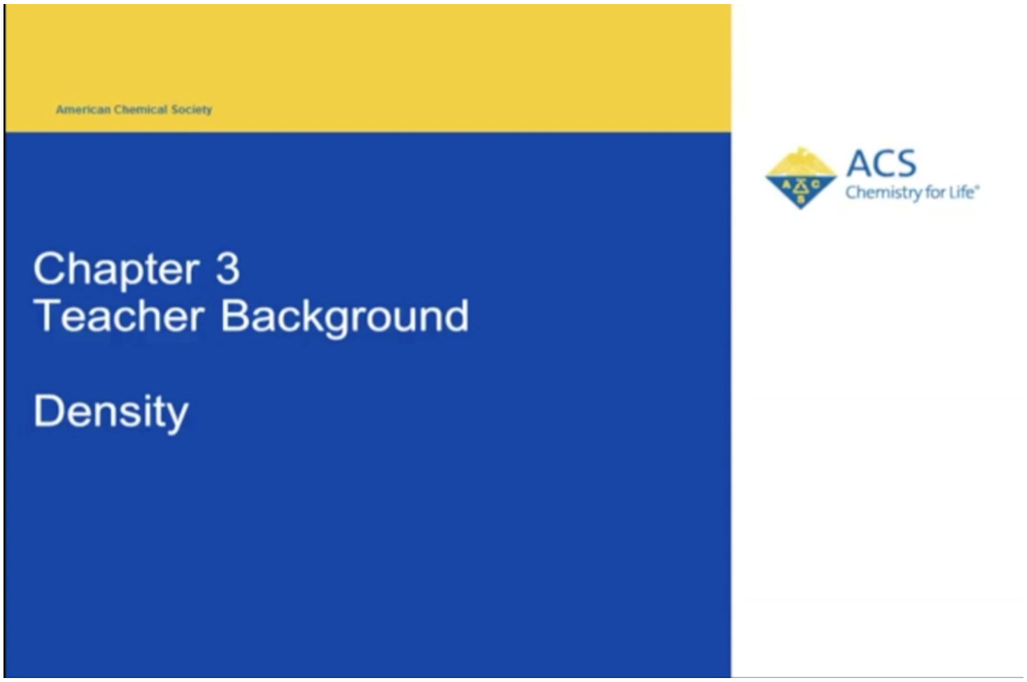
Prompt: *Do you know a rule, or set of rules, that can be used to make predictions about whether an object will sink or float in water? If so, describe the rule(s) below.*

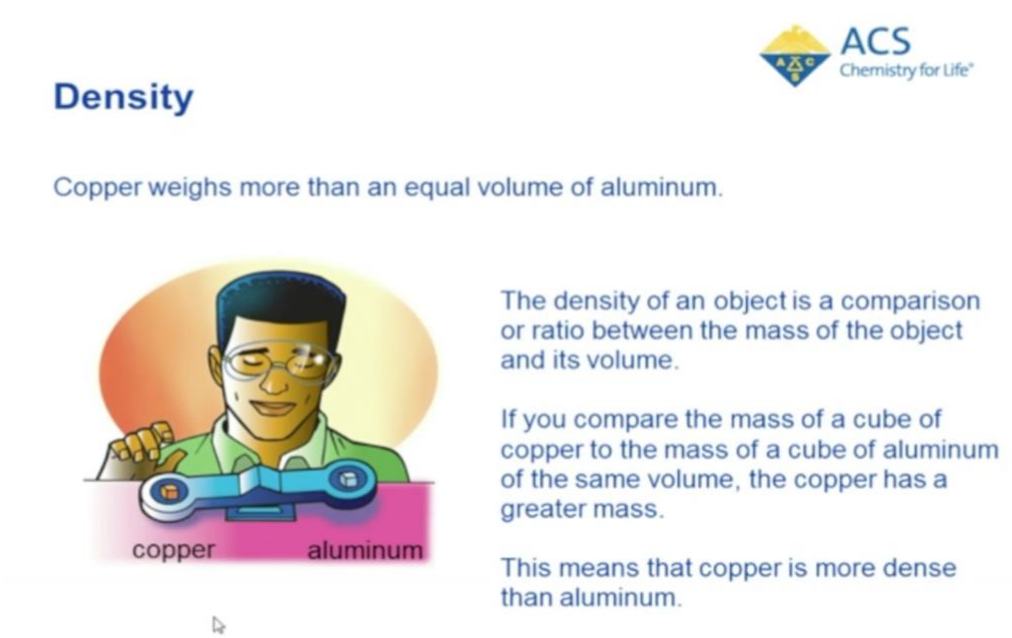
Score	Code	Response	Examples
0	DK	"Don't know" or similar response	"Not sure"; "I don't know"; "Can't remember"
1	MC	A rule that reflects superficial understanding ("Heavy objects sink" "light objects float"); or other "Misconception"	"If an object is heavy or made of certain materials"
2	Density-inaccurate	Mentions "density", but does not provide an accurate description or definition (can either be missing or inaccurate); may include a misconception about density; may say "mass and volume and material" but not explicitly use the word "density"	"It has to do with density" "More dense objects sink" (with no definition)
3	Density+water	Mentions "density", along with a rule related to sinking and floating in water (i.e. greater density of water = sink; less density float)	"If the object is more dense than water, it will sink; if it is less dense than water, float"

4	Density+definition	Mentions "density" along with an accurate description of the term; this might include "mass divided by volume" or "ratio of weight to size"; may discuss displacement of water; may or may not relate density of object to the density of water	"An object's density - if the density if greater than 1 g/ml, it will sink; less it will float"
5	Density+forces	Mentions "density" (or related term like buoyancy), along with rule and description of forces that cause objects to sink or float	"An object floats if the buoyant force is equal to the gravitational force; this depends on the mass of the object and how much water it displaces"

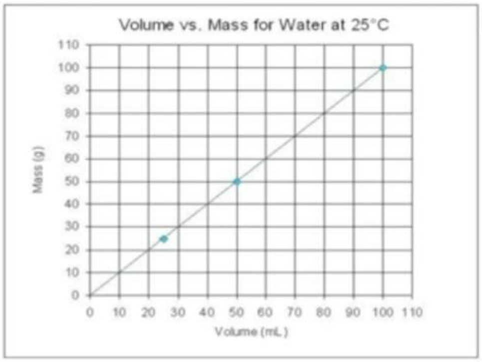
Appendix D: Direct Instruction Content for Experiment 2

Materials adapted from American Chemical Society.





Density of Water



The density of water is about 1 gram/cm^3.

100 mL has a mass of 100 g.
50 mL has a mass of 50 g.
25 mL has a mass of 25 g.

Lesson 3.4 – Sink and Float

Phenomena students observe:
- Although the candle weighs more than the clay, the candle floats and the clay sinks.

Question to investigate:
- How can a heavy object float and a lighter object sink?

Science concepts covered:
- An object floats if it is less dense than water.
- An object sinks if it is more dense than water.
- The density of a substance is based on the mass, size, and arrangement of the atoms it's made of.

Comparing Wax to an Equal Volume of Water

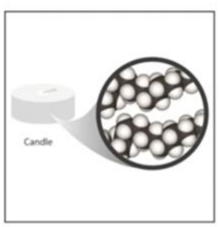
Compare the mass of the wax to the mass of an equal volume of water.

Since you are comparing the same volume, the one that has more mass must be more dense.

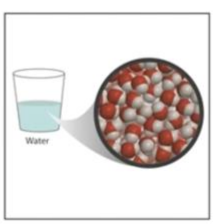
The one with less mass must be less dense.

Since the wax is less dense than water, the wax floats on the water.

Wax and Water on the Molecular Level

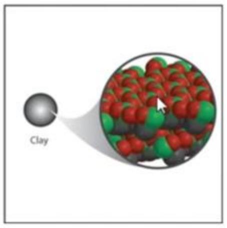


Wax:
Made of hydrogen atoms and carbon atoms.
They are very light.
Molecules are long and intertwined.

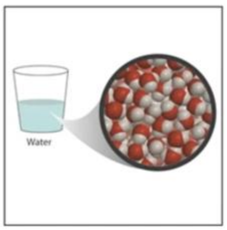


Water:
Made of hydrogen and oxygen atoms. The oxygen is heavier and a little smaller than carbon.
Molecules are very close together.

Clay and Water on the Molecular Level

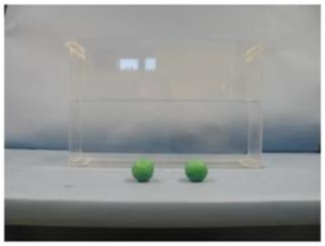


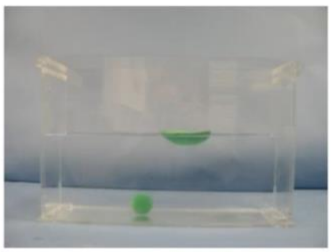
Clay:
Made from heavier atoms like aluminum and silicon.
Packed very close together.



Water:
Made from hydrogen and oxygen atoms which are light compared to those in clay.

How Can a Clay Object Float?





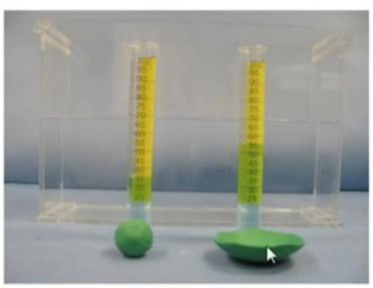
Clay is more dense than water so clay should sink.

An object like a clay ball or a clay cube does sink.

But, if you increase the volume of the clay object into a large enough bowl, the clay bowl can float.

Why?

Changing the Shape Can Change the Volume



The mass of the clay bowl is the same but the volume is increased enough that the overall density decreases.

If you compare the volume of the ball and the volume of the bowl, using the water displacement method, the bowl displaces about 50% more water than the ball.

So when the volume gets large enough, the density decreases enough so that it is less dense than water – so the bowl floats.

When the volume is large enough, the mass of water displaced by the object is great enough to equal the mass of the object. Then the object floats.